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# Essays on Macroeconomics

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# Essays on Macroeconomics

by

Helu Jiang

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ABSTRACT OF THE DISSERTATION

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Doctor of Philosophy in Economics

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Professor Ping Wang, Chair

*Cohabitation, Marriage, and Fertility: Divergent Patterns for Different Education Groups*. The United States has been experiencing a long-term decline in the rates of marriage and fertility and a steady rise in cohabitation. Contradicting the prediction of standard theory that emphasizes the opportunity cost of childrearing from labor market and gender specialization, skilled females have experienced a less pronounced drop in marriage and fertility, while unskilled females have experienced a more evident increase in cohabitation. I propose the following mechanisms to understand this puzzle: for high-skilled females, the higher implicit return of investment in children's human capital compensates for part of the growing opportunity cost of childrearing; a significant income effect from positive assortative matching dominates the conventional wage channel; and when childrearing resource cost increases, a strong selection effect exists whereby those with strong fertility motives shift into marriage. To quantitatively discipline the relative importance of different factors, I theorize the trade-off between market work and childrearing activities by examining decisions about consumption, marital status, and fertility. Counterfactual exercises show that 34.81% of the rise in cohabitation and 42.42% of the drop in marriage for the skilled can be explained by the rising returns of children, and 38.06% and 40.07%, respectively, for the unskilled. In addition to the returns of children, rising childrearing cost plays a significant role in explaining the declining fertility rates, contributing to 90.96% and 50.79% of the drop in fertility

for the two skill groups. Most of the shrinking cohabitation gap and widening marriage gap between the two skill groups can be attributed to the rising wage and skill premium, increasing childrearing costs, and the growing returns of children.

*Skill Biased Entrepreneurial Decline.* The U.S. is undergoing a long-term decline in the rate of firm startups. We find that this slowdown in entrepreneurship is more pronounced for skilled individuals. In particular, between 1985 and 2015 entry into entrepreneurship declined by 21% for those with at least a college degree and increased by 11% for those with a high school degree or some college experience. We posit that this skill biased entrepreneurial decline is a response to the changing income structure of workers and entrepreneurs that occurred over the same period. In support of this view, we find that, for skilled individuals, entrepreneurial income grew more slowly than worker's income while for unskilled individuals both incomes grew at relatively similar rates. We also provide evidence for entrepreneurial polarization consistent with wage polarization. To quantify the impact of income structure on entrepreneurial entry we develop a simple heterogeneous-agent, occupational choice model which takes as given a rising worker skill premium, driven by skill biased technical change. In the model, the rising worker skill premium can account for around two-thirds of the changes in entry among skilled and unskilled individuals. This paper contributes to understanding the forces behind the broader decline in business dynamism in the U.S. and suggests an integral role of rising income inequality.

*The Timing of Childbearing: Theory and Quantitative Analysis.* As significant as the shift from quantity to quality in fertility decisions, a rise in the age at first birth has been commonly observed in the more developed world. This paper attempts to understand such demographic trend both theoretically and empirically. We develop a continuous-time life-cycle model, in which a married woman decides when to have her first child and how she allocates her time to human capital accumulation and market activity. We then calibrate the benchmark model using data from CPS and generalize the model to allow for hetero-

geneous skill levels. We find that fertility-related productivity loss and job security play a more important role than the conventional human capital channel in terms of explaining the childbearing timing differentials between skill groups, and women are more sensitive to changes in fertility preference as opposed to leisure loss. Compared with high-skilled women, low-skilled women are more vulnerable to changes in labor productivity, human capital, husband's income, utility derived from children and the disutility in raising children. As a result, low-skilled women push up or defer their timing of childbirth more relative to high-skilled women.

# Chapter 1

# Cohabitation, Marriage, and Fertility: Divergent Patterns for Different Education Groups

Helu Jiang

## 1.1 Introduction

The United States has experienced significant behavioral changes that affect the family structures over the past few decades: the rates of marriage and fertility have dropped dramatically, accompanied by a pronounced increase in cohabitation. This paper documents the puzzle in divergent marital and fertility patterns between skill groups, finding that the decline in marriage and fertility is less dramatic for high-skilled females while the rise in cohabitation is more dramatic for low-skilled females. To understand the underlying driving forces leading to such differences, I build a model that features trade-offs between private consumption, public good consumption, and utility from children in which marital choices and fertility decisions are determined jointly.

Many early discussions have been focused on the increase in the age at first marriage, greater instability leading to “retreat from marriage" and delay in childrearing decisions. However, one striking fact that is often ignored is the rising trend of cohabitation. Figure 1.1, borrowed from Fitch et al. (2005), shows the number of cohabiting households nearly doubled from 1960 to 1970, and now, cohabitation has become a common living arrangement[1]. It is of great importance to take cohabitation into consideration when studying family structures. Moreover, using data from the Current Population Survey, I find that skilled females with at least a bachelor's degree have experienced a less pronounced drop in marriage and fertility rates, while unskilled females have experienced a more evident increase in cohabitation, as shown by Table 1.1. In the 1980s, 79.8% percent of unskilled females aged between 40 to 45 years old were currently married; this number dropped to 64.3% in 2008; for the skilled, the marriage share declined from 80% in 1980 to 74.9% in 2008; fertility dropped by 23.5% and 15.6%, respectively, over the same period. Cohabitation increased from 2.82% and 1.75% in 1995 to 5.63% and 3.41% in 2008 for the skilled and the unskilled. These facts challenge the standard theories that emphasize the opportunity cost of childrearing from labor market and gender specialization.

The traditional theory, stemming from Becker's sequences of work[2], emphasizes the sources of gains of marriage from specialization and posits that marriage is rationalized as a lifetime contract between a man and a woman, in which the man performs market work while the woman performs home production. As an increasing number of women is able to get access to higher education and participate in the labor market and the gender gap narrows[3], marital surplus falls with reduced specialization. In response to these underlying

[1]POSSLQ means Persons (or Partners) of Opposite Sex Sharing Living Quarters.

[2]See Becker (1973), Becker (1974), Becker (1981).

[3]Blau and Kahn (2017) provides a thorough review of the trends and explanations of evolution of gender wage gap.

changes in the economy, the divorce rate has also been increasing, along with the declining marriage rate and fertility rate (Lundberg et al., 2016). However, although the standard theories can explain the aggregate trends of declining marriage and fertility and rising cohabitation, they cannot fully explain the puzzle in divergent marital and fertility decisions between skill groups.

The rising income inequality between college-educated individuals and non-college-educated ones implies that high-skilled females not only face a higher opportunity cost of childrearing and a lower gender specialization gain from marriage, but they also experience a growing opportunity cost and a decreasing benefit from marriage. In this case, singlehood and cohabitation should have become more desirable for the skilled. Not only the wage gap is widened, but the income volatility also increases, especially for the less-educated households[4]. Facing a more volatile income stream, the unskilled should have found it more attractive to live with a partner for risk-sharing purposes than the skilled. Hence, it is often taken for granted that there should be more educated females who are less likely to get married or have children, which is contradictory to the divergent patterns found in data.

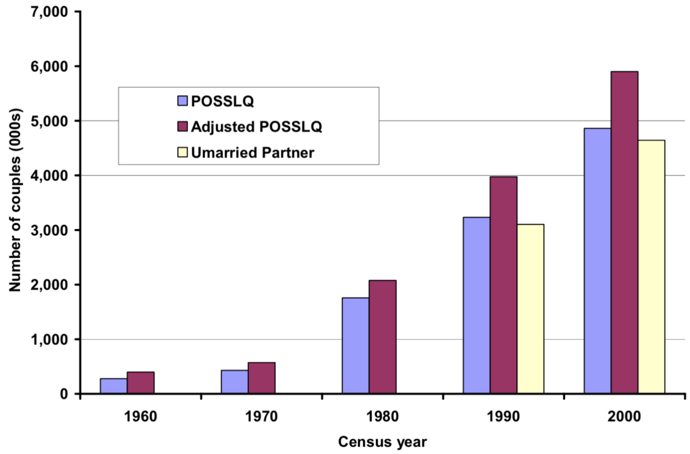
To understand the puzzle of the divergence of marital shares and fertility rate between skill groups, I propose the following four important mechanisms. First, a higher return of investment in children's human capital partly compensates for the high opportunity cost of childrearing for the skilled, and thus the skilled face a trade-off between external return from the labor market and implicit return from investment in children's quality. Data from the American Time Use Survey support this claim that educated women not only spend more time working in the outside labor market, but also invest more time in their children. Over the 2003 to 2006 period, the growth rate of time spent on childcare also increases with educational attainment. Second, the income effect from positive assortative matching dominates

[4] Dynan et al. (2012) claim that households including individuals who do not a college degree have consistently experienced more volatile incomes than households with members who have a college degree. More importantly, increases in income volatility are somewhat greater among less-educated households.

the conventional gender specialization effect for the skilled. Unlike low-skilled females, who retreat from marriage to cohabitation when facing a higher wage rate that is predicted by the conventional wage channel, high-skilled females benefit more from assortative mating because of income effect, and this increases the attractiveness of marriage when wages rise. Third, as childrearing cost goes up, the low-skilled group shifts from marriage to cohabitation and has fewer children. Nevertheless, selection effect is strong for the high-skilled group that those who have really strong fertility motives deviate from singlehood or cohabitation to marriage because the benefit associated with childrearing activities in marriage status will offset part of the increase in the cost. Last, marital and fertility decisions will also be affected by the level of the potential partner's commitment and people's preference toward different living arrangements. How much the partner contributes to the household will affect a female's choice on family formation. Skilled females and unskilled females may react differently to a change in the partner's commitment level because of different utility associated with public good consumption. Moreover, changes in legal treatments aiming to protect vulnerable parties in cohabiting relationships increase the acceptance of cohabitation.

In the model, female agents are heterogenous in their skill type, human capital, and type of potential partner they will meet. They choose their marital status and the number of children they want to have and allocate their time and resources to labor work, public good production, and educating children. The matching market is exogenous that a positive assortative matching process is assumed. The efficiency of investment in children's human capital will depend not only on the female's own human capital and effort invested, but also on choices of marital status. Turning to the quantitative analysis, I calibrate the benchmark model to the U.S. economy by targeting average marital shares and fertility rate for two skill groups from 1995 to 2008. The model can well capture the within-skill-group fertility rates in different marital statuses and between-skill-group fertility differentials. Two sets of counterfactual experiments are performed. The first set is designed to understand how different factors affect two skill groups differently. It is important to see the interactions of income effect, substitution effect, quantity-quality trade-off, and selection effect. The second set of experiments is conducted in a dynamic setting in which I divide the sample into two sub-periods and restore the value of parameters of interest in the second sub-period to its value in the first sub-period. Counterfactual exercises show that rising childrearing cost and return in children play a significant role in explaining the declining fertility rates for two skill groups. In terms of changes in marital shares, return in children contributes to 34.81% of the rise in cohabitation and 42.42% of the drop in marriage, and 38.06% and 40.07%, respectively, for the unskilled. In addition, high-skilled females are more sensitive to rises in their partners' commitment and cohabitation preference, while low-skilled females are more vulnerable to rises in wage and childrearing cost. Because of the higher return of investment in children's quality, higher benefit from positive assortative matching, and strong selection effect faced by the skilled, rising skill premium and childrearing costs have opposing effects on the two skill groups. The shrinking cohabitation gap and widened marriage gap between the two skill groups are largely explained by the rising wage and skill premium, increasing childrearing costs, and growing return in children. Three channels together contribute to around 165.8% of the increasing marriage differentials between skill groups, and partners' commitment together with cohabitation preference attributes to negative 65.8%.

Figure 1.1: Number of Cohabiting Households in the United States




Source: Fitch et al. (2005)

Table 1.1: Changes in Marriage Share, Cohabitation Share, and Fertility Rate

| | Marriage (1980-2008) | Cohabitation (1995-2008) | Fertility (1980-2008) |
|---|---|---|---|
| High-skilled | -6.39% | 94.81% | -15.59% |
| Low-skilled | -19.46% | 100.06% | -23.50% |

Source: CPS June Supplement

### 1.1.1 Literature

This paper is related to several themes of research. The first related field is the study on economics of marriage and the evolving role of marriage. Back in the 1970s, Gary Becker (Becker (1973), Becker (1974)) developed the economic model of marriage. He rationalized the marriage between a man and a woman as a lifetime contract in which the man provides income from market work and the woman provides household work such as cooking, childcare, and house cleaning. The expected source of gains of marriage stemmed from specialization and exchange (Becker, 1981). Later work has recognized gains from joint consumption of public good such as children and housing (Lam, 1988). Another approach to the study of marriage is the bargaining model. For example, Manser and Brown (1980) and McElroy and Horney (1981) developed the divorce-threat bargaining model, in which distribution within the marriage is treated as the solution to a cooperative game, the threat point of which is usually divorce. Empirically, Lundberg and Pollak (2015) investigated the evolving role of marriage in the United States. Since the focus of this paper is not on the distribution within marriage or the matching process between two parties, similar to De La Croix and Doepke (2003) and Doepke (2004), I follow a more macro approach by modeling the choices of female agents, abstract from matching market.

In most early works, cohabitation is not explicitly considered a possible living arrangement. Empirically, it is also hard to measure cohabitation due to data limitations. Researchers at the Census Bureau started developing national representative estimates of the number of cohabiting couples in the late 1970s (Glick and Norton (1977), Glick and Spanier (1980), Glick (1984), Bumpass and Sweet (1989b)). The measure known as Partners of the Opposite Sex Sharing Living Quarters (POSSLQ) was developed to infer cohabiting couples indirectly from the data. Later Casper and Cohen (2000) refined this measure into the adjusted POSSLQ to improve the estimates. Later in the 1980s and 1990s, with more data available, researchers started to investigate the emergence of cohabitation using either direct measures or indirect inference tools. Manning (2013) provides a detailed review of the related empirical literature. Not until 1995 did the CPS start to report cohabitation information by providing the relationship of an individual to the head within the same household[5]. CPS data provide a more precise measure for cohabitation than using POSSLQ. For example, from the survey questions, now it is possible to differentiate cohabiting couples from roommates sharing a space. Another stream of literature that studies cohabitation investigates the wealth accumulation (Vespa and Painter, 2011), happiness, and influence of different

[5]This paper only considers opposite-sex cohabiting and married couples. I understand that it is important to study same-sex partners, but this is not my main interest since less than 2& of unmarried couples are same-sex in the original data set.

family structures on children (Thornton (1988), Bumpass and Sweet (1989a), Bumpass and Lu (2000)). I contribute to this literature by studying the puzzle of divergence of marital choices between skill groups, and I take cohabitation as a serious living arrangement as opposed to singlehood and marriage.

An important focus of this paper is people's fertility decisions, including both the intensive and the extensive margins. I not only study whether a female decides to have kids or not, but also study the quantity and quality trade-off. Advanced by Becker (1960), Becker (1973), and Willis (1973), economists who study modern economic demography concentrate on parental trade-offs between the number and quality of children. Hanushek (1992) provides empirical evidence that family size directly affects children's achievement. This paper contributes to the theory by providing a new channel that considers the return of investment in children's human capital to explain different behaviors across skill groups. To reinforce this idea, educated females face a high opportunity cost of childrearing and enjoy a high return of educating their kids, thus leading to a trade-off between market work versus childbearing activities.

This work is also related to studies on inequality, gender gaps, and female labor market performance. Barro and Becker (1989) apply the framework of altruistic parents making choices about family size together with consumption decisions and intergenerational transfers to a closed economy, extending the optimal economic growth literature by allowing optimal choices about fertility and intergenerational transfers. Galor and Weil (1993) link the gender gap with fertility and investigate the impact on aggregate growth in the economy. Although my paper is not directly discussing economic growth, it is essential to study how labor market conditions and rising inequality affect women's choices on family formations. Several recent papers discuss that marital and fertility patterns differ among different groups. Greenwood et al. (2016) document that the drop in marriage and the increase in divorce are greater for non-college-educated individuals versus college-educated ones. They construct a unified model of marriage, divorce, educational attainment, and female labor force participation. However, cohabitation and fertility are not part of the picture, which are the major focus of this paper. Bar et al. (2018) study the flattened relationship between income and fertility, proposing the marketization of parental time costs as the driving force. They focus on the income effect for the high-income women and marital sorting. What is different in this paper is that an assortative matching process is assumed to be fixed overtime. I want to avoid getting into the debate about whether such assortative mating has increased. The income effect increases the attractiveness of marriage for high-skilled females because of the positive assortative matching. This paper has shed light on understanding how income inequality and changes in labor market conditions shape females' decisions about family structures and fertility.

The most closely related paper is by Lundberg et al. (2016). They use data from 1960-2000 U.S. censuses and 2010 American Community Survey to document divergent patterns in marriage, cohabitation, and childbearing. They also discuss the changes in gender roles, marital surplus, and investments in children. Two crucial aspects of this paper are different from theirs. First, in the empirical part, I restrict the sample to females aged from 40 to 44 because this paper focuses on lifetime choices instead of dynamic transitions and I believe this age restriction better captures the completed fertility. Second, Lundberg et al. (2016)'s paper is an empirical work. In contrast, I develop a theory to rationalize the importance of return of investment in children's quality. By performing counterfactual experiments, I am able to determine the relative importance of different forces behind the model.

## 1.2 Empirical Findings

I follow Lundberg et al. (2016) in considering only high school graduates and those with bachelor's degrees or above. To be more specific, the low-skilled group is defined as the sample of females with high school degrees, including individuals with some college experience but no bachelor's diploma. The high education group is defined as women with at least a bachelor's degree. I further restrict the sample to females aged between 40 to 44 since this age group is close to the end of females' fecundity cycle, thus providing a more precise measure for completed fertility rate. For the majority of the empirical results, I take data from the Current Population Survey (IPUMS CPS)[6]. I focus on the time periods starting from 1980 to 2008. Year 1980 is the earliest year for which I can get reliable data, and year 2008 is chosen as the ending period because the Great Recession is not the focus of this paper. Not until year 1995 did cohabitation data become available, and hence any analysis using cohabitation data starts from that year.

I first present empirical findings on divergent marital choices and fertility decisions between low-skilled and high-skilled groups, and then I provide evidence on the trade-off between outside opportunity cost of childbearing working in the labor market and implicit return of investment in children.

### 1.2.1 Evolution of Marital Status

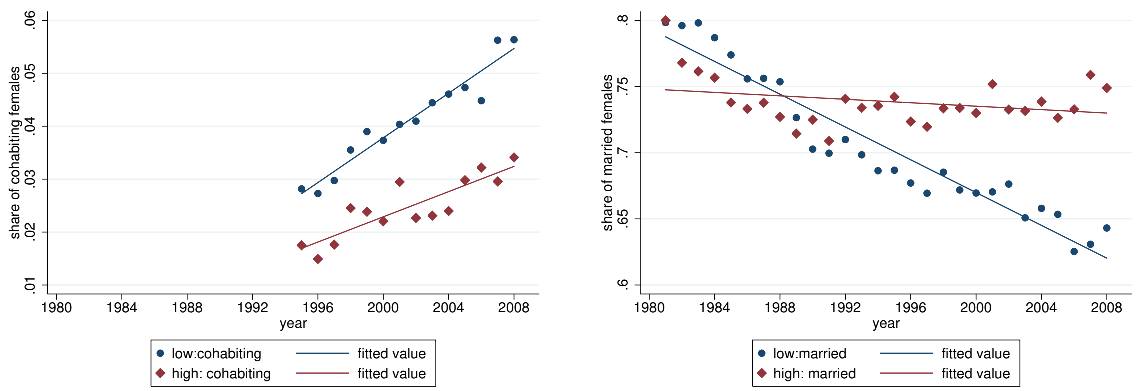
Figure 1.2 and Figure 1.3 illustrate the evolution of marital choices by education groups. In the 1980s, 79.85% percent of unskilled females aged between 40 to 45 years old were currently married; in 2008, this number dropped by 19.46% to 64.31%; for the skilled, the marriage share declined by 6.39% from 80.01% in 1980 to 74.90% in 2008. The cohabitation share rose from 2.82% and 1.75% in 1995 to 5.63% and 3.41% in 2008 for the unskilled and the skilled, and the increase was 99.65% and 94.86%, respectively. Despite the fact that both skill groups have experienced a sharp drop in marriage and a steady rise in cohabitation, the changes are more dramatic for the unskilled.

The group "unpartnered" is defined as the union of females who are currently separated,

[6]See appendix 1.9.1 for further discussion of June CPS Supplement and March CPS Supplement.

divorced, or widowed and females who have never married, also denoted as "single" in this paper. The declining rate of being unpartnered for the highly educated females is mostly driven by the declining rate of being separated, divorced, or widowed because the single share posits a positive trend. The divergent pattern is observed here that the single share rose from 3.89% to 11.13% for the unskilled, and this increase is much less dramatic than that for the unskilled, which grows from 7.55% to 10.32%[7].

Figure 1.2: Marriage Status for Females by Education Groups (40-45 years old)




(a) currently cohabiting (b) currently married

Source: June CPS Supplement

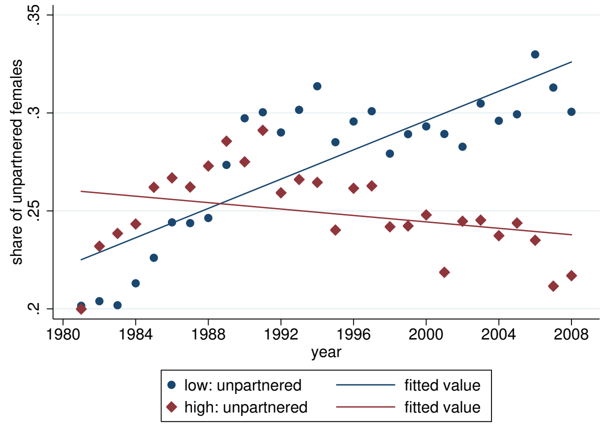
### 1.2.2 Evolution of Fertility

Next, let us look at the evolution of fertility rates over time. Fertility rate is defined as the average number of children ever born over the female sample aged between 40 and 44 years old conditional on having at least one child[8]. Figure 1.4 shows the declining aggregate trend

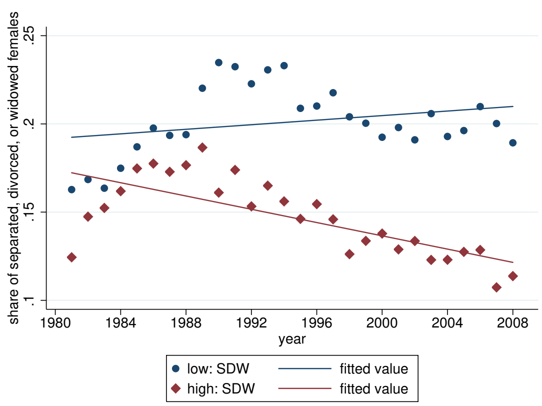
[7] Appendix 1.9.2 provides figures on detailed evolution of marital status by fertility decision.

[8] There are multiple ways to calculate fertility rates. Completed fertility is the average number of children born to women belonging to the same cohort once they have reached the end of their reproductive life. General fertility is defined as births per 1000 women aged over the total female sample. Total fertility is the hypothetical lifetime births per woman. Completed fertility is chosen here because (1) this age group is toward the end of a female's fecundity cycle, (2) fertility questions in the CPS June Supplement are asked of females aged 15-44 years old in most sample periods of interest, (3) childrearing timing decision or marital status transition is not my main interest, and (4) the zero-mass issue is not a major emphasis in this paper.

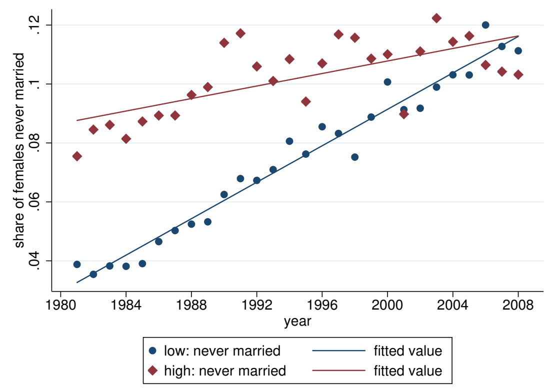
Figure 1.3: Marriage Status for Females by Education Groups cont. (40-45 years old)




(a) currently unpartnered




(b) currently separated, divorced, widowed

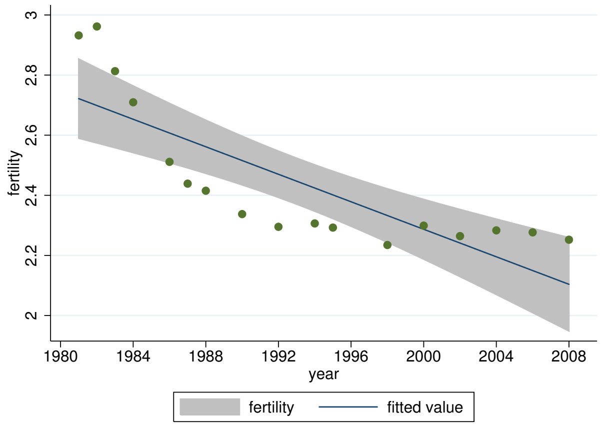



(c) never married (single)

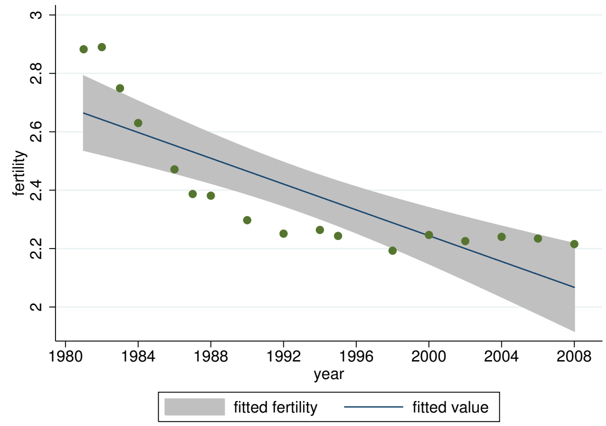
Source: June CPS Supplement

of fertility. The left panel is the naive measure, while the right panel shows the average predicted fertility from the OLS regression in which I control for a quartic in age, education, experience, race dummies, state dummies, and industry dummies. A more detailed report of changing rates of fertility by education groups can be seen in Figure 1.5. The fertility rate dropped by 23.5% from 3 to 2.3 and 15.6% from 2.6 to 2.2 for the two skill groups conditional on having children. Again, despite the common declining rates in fertility experienced by two skill groups, the drop is more dramatic among the low-skilled.

Figure 1.4: Completed Fertility Rate over Time



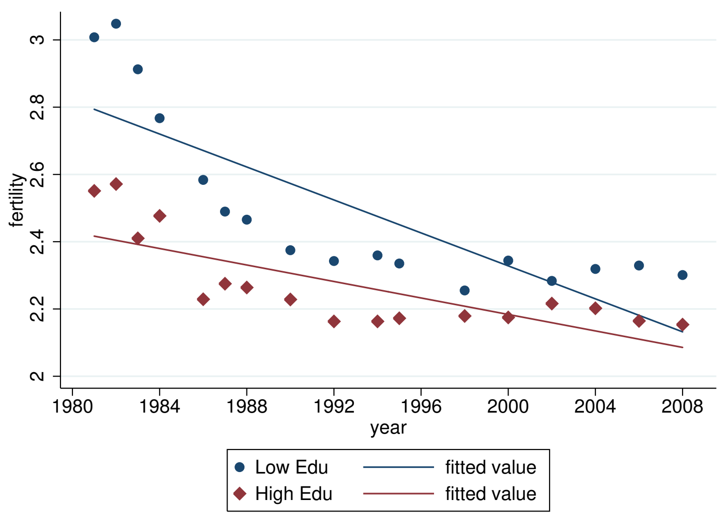

(a) naive measure




(b) regression measure

Source: June CPS Supplement

Figure 1.5: Completed Fertility Rate over Time by Education Groups




Source: June CPS Supplement

### 1.2.3 Fertility Choice vs. Marital Decision

The previous two sections document the fact that the two skill groups posit different trends of evolution in family structures and fertility decisions. This section shows that it is important to understand that decisions about living arrangements and childrearing are closely related. Table 1.2 and Table 1.3 examine how fertility choice is related marital decision[9].

In Table 1.2, the average marginal effect from the PROBIT regression on whether a woman has at least one child or not is reported, with age, a quartic term in age, occupation, industry, race, and state dummies controlled. The coefficients in the first and second row imply that compared to single females, females who choose cohabitation are more likely to have at least one child, and married females have the highest probability of having children after controlling for demographic characteristics.

Table 1.3 reports the results from the OLS regression on fertility rate controlling for the same demographic variables. Conditional on having at least one child, married females tend to have the highest number of children among the three marital groups, and cohabitation group comes second. Although a strict casual relationship cannot be achieved from these two tables, the results imply that fertility decisions and marital choice are interrelated in the sense that people with various fertility motives may choose different living arrangements, and vice versa. Therefore, it is of great importance to study childrearing decisions and choices of different marital status together as a joint decision process.

[9]See Table 1.20 and Table 1.21 in appendix 1.9.2 for the results using being unpartnered as the base group

Table 1.2: Tendency to have children

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | birth | birth | birth | birth |
| cohabiting | 0.281*** | 0.276*** | 0.273*** | 0.274*** |
| | (0.0743) | (0.0737) | (0.0745) | (0.0745) |
| married | **1.734*** | **1.741*** | **1.737*** | **1.737*** |
| | (0.0296) | (0.0293) | (0.0296) | (0.0297) |
| bachelor+ | -0.351*** | | -0.351*** | -0.439*** |
| | (0.0222) | | (0.0222) | (0.0564) |
| Years | No | Yes | Yes | Yes |
| Years×Edu | No | No | No | Yes |
| Constant | 1.810 | -0.191 | 1.669 | 1.467 |
| | (11.03) | (10.96) | (11.03) | (11.04) |
| Observations | 22110 | 22110 | 22110 | 22110 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3: Completed Fertility

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | fertility | fertility | fertility | fertility |
| cohabiting | 0.192* | 0.188* | 0.194* | 0.199* |
| | (0.0914) | (0.0915) | (0.0914) | (0.0914) |
| married | **0.356***** | **0.340***** | **0.357***** | **0.359***** |
| | (0.0355) | (0.0355) | (0.0356) | (0.0356) |
| bachelor+ | -0.112*** | | -0.112*** | -0.124** |
| | (0.0169) | | (0.0169) | (0.0460) |
| Years | No | Yes | Yes | Yes |
| Years×Edu | No | No | No | Yes |
| Constant | -7.846 | -8.188 | -7.941 | -7.824 |
| | (8.018) | (8.029) | (8.020) | (8.019) |
| Observations | 17451 | 17451 | 17451 | 17451 |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

There are three takeaways from these empirical results: (1) on average, regardless of marital status, unskilled females tend to have more children than skilled females; (2) the fertility rate has dropped much less for skilled females; (3) divergence also appears in marital choices between two skill groups in that both the drop in marriage and the rise in cohabitation are more prominent for unskilled females. The first observation is consistent with quantity-quality trade-off theory that high-skilled females with higher incomes are more likely to invest in the quality of their children rather than the quantity. However, the puzzle comes from the second and the third observations, namely the divergence between the two skill groups.

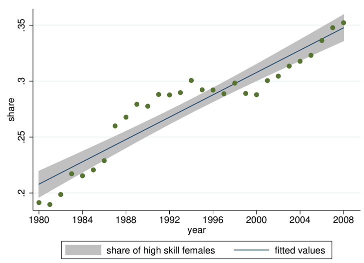
In the next two sections, I show that it is true that women now face a much higher opportunity cost of childbearing, and those with higher skills suffer an even higher cost because of rising skill premium. Nevertheless, females gain an implicit return from investing time with their children, although such a return may depend on different family structures. Therefore, females face a trade-off between outside opportunity cost and implicit return of investment in children's human capital, thus providing a novel channel to understand the puzzling different trends of marital shares and fertility rate between skill groups.

### 1.2.4 Labor Market for Females

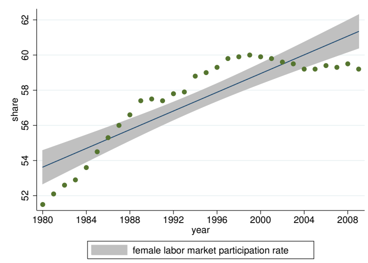
I follow Acemoglu (2002) in constructing the skill premium for females. The relevant measure of a worker's income is constructed from the IPUMS variables INCWAGE, which is the annual income reported in real 2010 USD. Those with no earnings and the remaining lowest 1 percent of earners are dropped from the sample. Top-coded incomes are assumed to be 1.5 times the top-code. The reported measure of skill premium is the coefficient on a dummy variable for those with at least a bachelor's degree (compared to those with only a high school degree or some college experience) in an OLS regression of log income with a variety of controls. The controls are (1) a quartic in years of potential experience, (2) race (white/non-white) dummy, (3) state dummies, and (4) additional dummies for educational categories. Years of potential experience $E = \text{age} - S - 6$ is defined by assuming that an individual's schooling starts after age six. Years of schooling, $S$, are assumed using the IPUMS variable EDUC. This variable reports the highest level of educational attainment of a respondent.

Figure 1.6 reports the changes in labor market for females from 1980 to 2008. Panel (a) illustrates the rising share of females who have higher education experience. The share of the high-skilled increased from 13.36% in 1980 to 35.33% in 2008. Panel (b) illustrates the striking increase in female labor market participation rate in that more and more women have engaged in market work. This features a decreasing gender pay gap and less discrimination (Hsieh et al., 2013). Panel (c) shows the rising skill premium. Higher return on skills leads to even higher outside cost for skilled females. Easier access to higher education and better labor market conditions imply that an increasing number of females are able to earn a higher return from the labor market; however, this also implies a higher opportunity cost of childrearing.

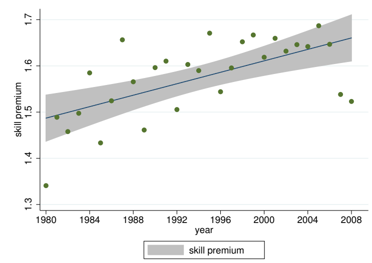
Figure 1.6: Labor Market for Females




(a) college+ share




(b) participation rate




(c) skill premium

Source: CPS March Supplement and FRED

### 1.2.5 Time Spent on Kids

Return of investment in children could take multiple forms: spending time with kids might give direct utility to parents, or some parents just love to be with their children; parents may care about the future income/future job/education of their children; and parents may directly get monetary support from their children. Hence, it is very complicated to measure such intangible implicit return of investment in children. Instead, here I provide supporting evidence of the time spent on children since it reflects how parents value time invested in different activities.

Table 1.4: Time Spent in Market Work and Child Care for Women (40-45 years old) in the United States by Educational Attainment

| | Marital Status | | | Market Work, hours/week | | Childcare, minutes/day | | | |
|---|---|---|---|---|---|---|---|---|---|
| Education | Unpartnered | Cohabiting | Married | total hours | main job | caring | education | health | total |
| high school | 27.47% | 4.46% | 68.06% | 25.512 | 23.229 | 29.757 | 8.942 | 1.092 | 39.794 |
| some college | 30.18% | 3.88% | 65.94% | 29.288 | 25.893 | 39.036 | 12.743 | 2.690 | 54.586 |
| BA and above | 23.14% | 2.92% | 73.94% | 30.017 | 26.591 | 62.158 | 15.303 | 2.141 | 79.648 |

Using the American Time Use Surveys from 2003 to 2008, I examine parental time allocated to childbearing activities[10]. As Table 1.4 shows, both the time spent on market work and childcare increases with years of schooling[11]. This is also supported by Guryan et al. (2008), who claims the relationship still holds even when controlling for employment status. He found that mothers with at least a bachelor's degree spend approximately 4.5 hours more per week on childcare than mothers with a high school degree or less. Given the fact that the higher-educated parents also spend more time working in the labor market, the striking finding that they are also more likely to spend time with their child/children implies that there must exist an implicit higher return for time invested in their children.

[10]Childcare activities include physical care for children, reading to/with children, playing with children (not sports), arts and crafts with children, talking with/listening to children, organization and planning for children, looking after children, attending children's events, waiting for/with children, picking up/dropping off children, and caring for/helping children. Activities related to household children's education include homework, meetings and school conferences, home schooling, and waiting associated with children's education. Activities related to household children's health include providing medical care, obtaining medical care, and waiting associated with children's health. See BLS website for more information.

[11]For detailed distribution of time use, see Figure 1.12, Figure 1.13, and Figure 1.14.

Table 1.5: Time Spent in Market Work and Child Care for Women (40-45 years old) in the United States over Time by Educational Attainment

| | total hours usually worked per week | | | total minutes spent on childcare per day | | |
|---|---|---|---|---|---|---|
| year | high school | some college | BA and above | high school | some college | BA and above |
| 2003 | 26.15 | 28.25 | 28.54 | 53.62 | 52.43 | 79.33 |
| 2004 | 26.63 | 29.57 | 29.30 | 32.74 | 53.21 | 74.97 |
| 2005 | 26.79 | 28.91 | 30.43 | 33.92 | 54.38 | 84.42 |
| 2006 | 24.36 | 30.06 | 31.83 | 38.89 | 55.34 | 69.25 |
| 2007 | 24.30 | 29.01 | 29.27 | 41.95 | 58.06 | 82.20 |
| 2008 | 24.23 | 30.10 | 30.53 | 37.27 | 54.60 | 87.40 |
| change | -7.35% | 6.52% | 6.96% | -30.48% | 4.15% | 10.18% |

What is more, over this period, high school graduates decrease both time spent in market work and time in childcare; on the contrary, females with at least some college experience devote more time into labor work and invest more in their children. As can be seen from the last row in Table 1.5, the growth rate of time spent on childcare also increases with educational attainment. Facing a higher wage and rising skill premium, the skilled females find it more profitable to work for longer hours in the market. At the same time, the fact that they also increase the time they spend on childcare implies that return from investment in children for the skilled is not only higher but also increases faster than that for the unskilled.

## 1.3 Benchmark Model

Female agents in the model are assumed to be heterogenous in three aspects: skill type, human capital, and type of potential partner. There are two skill groups in the economy, high-skilled (college-educated) or low-skilled (non-college-educated).

$$\mathbb{1}^{col} = \begin{cases} 1 & \text{high skill group denoted by } H \\ 0 & \text{low skill group denoted by } L \end{cases}$$

Within each skill group, agents are endowed with human capital $h$, following the distribution of human capital denoted by $F^H(h)$ and $F^L(h)$, respectively. In addition to the skill type and human capital, an agent is also endowed with an exogenous $\theta$ that governs the income of her potential partner, exogenously drawn from distributions $G^H(\theta)$, and $G^L(\theta)$. I abstract from the double-sided marriage market and assume the positive assortative matching process. Hence, the exogenous state of a female agent in the model can be described by $(\mathbb{1}^{col}, h, \theta)$.

In the model, each agent is endowed with one unit of time, and she values utility from private good consumption, utility over her children's human capital discounted by total number of children, and utility from public good consumption if she is in cohabitation or marriage status. She allocates the one unit of time to childrearing activities and working in labor market, and part of her labor income will be used for public good production if she chooses to cohabit or marry a partner. To summarize, she makes decisions about consumption ($c$), the lifetime quantity of children ($n$), effort invested in children's human capital ($q$), resources allocated to public good production ($s$), and public good consumption ($X$) with a subsistence level of consumption ($\underline{X}$). All these choices are continuous.

Raising a kid takes time and money. Hence, I model both the resource cost and time cost, denoted by $\pi_0$ and $\pi_n$, respectively. Educating a kid is a time-intensive activity. I denote the time cost by $\pi_q$. There would be a trade-off between quantity and quality of children. The human capital accumulation process for children depends on the parents' own human capital and the effort they invest in educating their children. Production of public good requires labor income contribution both from the female agent and her partner.

At the same time, the agent makes a discrete choice on marital status, including singlehood, cohabitation, and marriage, denoted by $M \in \{s, c, m\}$. To simplify notations, I also use three indictor functions to capture the endogenous marital decision: $\mathbb{1}^s = 1$ represents being single, $\mathbb{1}^c = 1$ cohabiting with a partner, and $\mathbb{1}^m = 1$ being married. The model is static in the sense that there is no breakup or divorce[12].

### 1.3.1 Household Utility

Omitting the subscript for individual $i$, the utility function of a female agent endowed with $(\mathbb{1}^{col}, h, \theta)$ is defined as follows:

$$
\begin{aligned}
U = \{ \quad & \frac{c^{1-\sigma_c}}{1-\sigma_c} + (\mathbb{1}^M \cdot \alpha_n^M) n^{\gamma} \big[ \frac{(nh')^{1-\sigma_n}}{1-\sigma_n} + \mathbb{1}^M \delta_n^M \big] \\
& + \mathbb{1}^c \cdot \alpha_X \frac{(X - \underline{X})^{1-\sigma_X}}{1-\sigma_X} + \mathbb{1}^m \cdot \alpha_X \frac{(X - \underline{X})^{1-\sigma_X}}{1-\sigma_X} \} \cdot (1 + \mathbb{1}^c \delta^c + \mathbb{1}^m \delta^m)
\end{aligned}
\tag{1.1}
$$

The utility function is assumed to take CRRA functional form, and the intertermporal preference parameters in the CRRA utility function are assumed to vary for private consumption $(\sigma_c)$, children $(\sigma_n)$, and public good $(\sigma_X)$.

All female agents in the model can choose to have kids. They decide how many children to have, and they care about the quality of their children. Hence, utility over children contains two parts: total human capital from children $(nh')$ and a fertility utility premium $(\delta_n^M)$. Following Becker et al. (1990), I assume both will be discounted by the total quantity of children that is governed by the parameter $\gamma$. The fertility utility premium is modeled to capture the fact that even if a parent does not invest any effort into children's human capital development, the presence of children will bring her happiness, although such happiness decreases with the number of children. Both fertility preference parameter $\alpha_n^M$ and fertility premium $\delta_n^M$ are assumed to vary across different marital statuses such that $\alpha_n^s < \alpha_n^c \leq \alpha_n^m$

[12]Note that variables or parameters with superscript $\{s, c, m\}$ imply that they are specific to marital groups, while those with superscript $\{H, L\}$ are skill-group specific.

and $\delta_n^s < \delta_n^c \leq \delta_n^m$, which is supported by the empirical evidence shown in section 1.2.3 that females who choose different living arrangements are associated with different fertility motives.

Cohabiting and married females are assumed to face the same public good preference parameter $\alpha_X$, while single women do not have the choice of enjoying public good. The subsistence level of public good consumption captures the idea of necessary joint expenditure for two partners, such as housing. Although there is no breakup or divorce in the model, direct utility cost/premium parameters $\delta_c$ and $\delta_m$ capture the net direct utility from cohabitation and marriage. For example, a negative $\delta_m$ implies that the cost associated with marriage, such as wedding cost or divorce cost, outweighs the benefit from marriage. The important point is that I do not put any parametric restrictions on these two parameters, and in the calibration part, I will let the model tell.

### 1.3.2 Budget Constraint

A skilled female worker gets a unit wage of $\omega^H$ while an unskilled worker gets a unit wage of $\omega^L$. The total wage a female agent gets is proportional to her own human capital.

$$\begin{aligned} w &= \omega h \\ &= [\mathbb{1}^{col}\omega^H + (1 - \mathbb{1}^{col})\omega^L]h \end{aligned}$$

The exogenous assortative matching process implies that if a female gets wage $w$, then she will meet a partner who earns $\theta w$. The budget constraints are written as follows:

$$c = w(1-s) \cdot \left[1 - (\mathbb{1}^s \pi_q^s + \mathbb{1}^c \pi_q^c + \mathbb{1}^m \pi_q^m) qn - \pi_n n\right] - \pi_0 n \tag{1.2}$$

where

$$\pi_n = \mathbb{1}^{col}\pi_n^H + (1 - \mathbb{1}^{col})\pi_n^L$$

$$\pi_0 = \mathbb{1}^{col}\pi_0^H + (1 - \mathbb{1}^{col})\pi_0^L$$

### 1.3.3 Human Capital Accumulation Process

Children's human capital partially depends on how smart their parents are and partially on how much effort their parents invest. Parameters $\tau$ and $\eta$ capture the relative importance nature versus nurture plays in shaping a person's human capital. Efficiency in educating children depends on family structures, which contention is supported by a vast of empirical literature[13]. Hence, I assume $\kappa^s < \kappa^c \leq \kappa^m$.

$$h' = H(q, h) = B \cdot h^{\tau} \cdot (\kappa^M + q)^{\eta} \tag{1.3}$$

where

$$B = \mathbb{1}^{col}B^H + (1 - \mathbb{1}^{col})B^L$$

$$1 > \tau, \quad \eta > 0, \quad \tau + \eta \leq 1$$

### 1.3.4 Public Good Production

If a female agent decides to cohabit with or marry a partner, she can enjoy a public good with her partner, but she needs to allocate fraction $s$ of her market work value to public good production. Simultaneously, her partner contributes $s^M_{man}$ portion of his income $w_{man} = \theta \cdot w$ to public good production. Nevertheless, if a female agent chooses singlehood, she does not

[13] There is a considerable amount of empirical literature that documents the benefits of marriage for the well-being of children. On average, children living with two biological married parents tend to experience better educational, cognitive, and social outcomes not only in the short-term but also through adulthood (Artis (2007), Broman et al. (2008), Brown (2004), Carlson and Corcoran (2001), Manning and Lamb (2003), Teachman (2008), Videon (2002), Amato (2005)). Several works have also been conducted to use theories to explain the relationship between family structures and the well-being of children. Potential theoretical explanations include economic resources, parental socialization, family stress or turbulence, and selection (Amato (2005), Carlson and Corcoran (2001), Huston and Melz (2004)). See Brown (2010) for a detailed literature review.

have the option to consume public good. Production of public good takes the following form:

$$\begin{cases} X^c = \left\{[ws(1-\pi_q^c qn - \pi_n n)]^{\rho^c} + (w_{man}s_{man}^c)^{\rho^c}\right\}^{\frac{1}{\rho^c}}/\xi \\ X^m = \left\{[ws(1-\pi_q^m qn - \pi_n n)]^{\rho^m} + (w_{man}s_{man}^m)^{\rho^m}\right\}^{\frac{1}{\rho^m}}/\xi \end{cases} \tag{1.4}$$

Notice that $\xi$ captures the possibility for a female to meet a partner with negative asset (positive debt or liability) even if the partner has a positive income value. I assume $\xi^H = \xi^L = 2$ for the benchmark case.

### 1.3.5 Maximization Problem

The maximization problem can be solved in two steps. First, conditional on marital status, a female agent chooses private consumption $c$, number of children $n$, effort invested in children's human capital $q$, fraction devoted to public good production $s$, and public good consumption $X$ to maximize utility (equation 1.1) subject to the budget constraint (equation 1.2), facing human capital accumulation process of their children (equation 1.3), and public good production (equation 1.4). Then she compares the total utility when choosing different marital status including singlehood, cohabitation, and marriage, and then she will choose the one that gives her the highest utility ($M^*$). The formal maximization problem is written as follows:

$$\textbf{step1:} \quad V(M) = \max_{c\geq 0, n\geq 0, q\geq 0, 1\geq s\geq 0, X\geq \underline{X}} U$$

subject to

budget constraint (1.2)

human capital accumulation process for children (1.3)

public good production (1.4)

$$\textbf{step2:} \quad M^* = \underset{M\in\{s,c,m\}}{\text{argmax}} \quad V(M)$$

## 1.4 Calibration Strategies and Results

Since data on cohabitation in the CPS did not become available until year 1995 and the emphasis of this paper is not on the Great Recession, I only consider the time period from year 1995 to year 2008.

For potential partner's income and contribution to the production of public good, I assume the following functional forms that the time a partner contributes to the public good will be proportional to the time the female agent contributes:

$$w_{man} = \omega h \cdot \theta = \omega h \cdot [\mathbb{1}^{col}\theta^H + (1 - \mathbb{1}^{col})\theta^L]$$

$$s^c_{man} = s(1 - \pi^c_q qn - \pi_n n) \cdot \overline{s^c_{man}}$$

$$s^m_{man} = s(1 - \pi^m_q qn - \pi_n n) \cdot \overline{s^m_{man}}$$

There are thirty-seven parameters in total, out of which two parameters will be taken from the existing literature, six parameters are chosen arbitrarily, and the remaining are either estimated from the data or calibrated jointly from the model. All the parameters are presented in Table 1.6.

The intertermporal preference parameters in the CRRA utility function are assumed to vary for private consumption, children, and public good, but all lie within the range from zero to one. However, there is no consensus on what the value should be for different consumption good or utility for children. The parameters $\sigma$ in the CRRA utility function that governs the intertemporal preference on overall consumption are set to be 0.68 in Hanushek et al. (2014). Greenwood et al. (2003) set the value to be 0.5 for public good, 0.325 for utility on quantity of children, and 0.2 for utility on quality of children. In the benchmark model, I set the intertemporal preference parameter toward private consumption, public good, and utility over children to be 0.6, $\frac{2}{3}$, and $\frac{3}{4}$, respectively. To have a valid utility function, I should have $\sigma_n - 1 < \gamma$ and $\gamma < \sigma_n$, and hence I arbitrarily set $\gamma = 0.6$. The parameters, $\rho^c$ and $\rho^m$, that govern the substitutability between female's and male's contribution to public good production are assumed to be 0.5.

Two parameters that shape the human capital accumulation process are taken from De La Croix and Doepke (2003). $\tau$ measures the intergeneration human capital transmission, while $\eta$ governs the transmission of parents' investment into children's human capital.

Twelve parameters are estimated from data. From Expenditures on Children by Families (CRC), I estimate the childrearing resource cost for the median income family and subtract 25% to adjust for families with more than two children. Subsistence level of public good, $\underline{X}$, is estimated using housing consumption out of total consumption, which ranges from 30% to 35%. I choose 30% for the benchmark model. The ratio of time contribution between partners is estimated from Time Use Survey for married and cohabited couples. Partners in cohabitation relationships on average contribute more to household work than those in marriage, which supports the existence of the story of specialization[14].

[14]Household activities include 9 categories: (1) housework (interior cleaning, laundry, sewing, storing items, other housework), (2) food and drink preparation, presentation, and cleanup, (3) interior maintenance, repair, and decoration, (4) exterior maintenance, repair, and redecoration, (5) household activities

Both the skill premium and the share of different human capital groups are estimated from the pooled Current Population Survey (CPS). The high-skilled group is defined as individuals with at least a bachelor's degree, and the low-skilled group is defined as those with high school degrees. High school dropouts are not included in the sample to be consistent with the fertility and marital shares data described in the previous paragraphs. As discussed in the previous section, I follow Acemoglu (2002) in constructing the skill premium.

For the distributions of human capital and types of potential partners, I use wage data from CPS to estimate distributions for low- and high-skilled groups separately. Analogously, I restrict the sample of females aged from 40 to 44. Wage is constructed using the IPUMS variable INCWAGE, and the lowest 1 percent of earners is trimmed off. Top-coded incomes are assumed to be 1.5 times the top-code. Using the IPUMS variable SPLOC, I am able to link family members within a household, and that is how I estimate the husband-to-wife income ratio, which corresponds to its counterpart in the model-parameter $\theta$. I assume the functional form for human capital distribution and partner type distribution to be log-normal. For illustration purpose, Panel (a) in Figure 1.7 is restricted to those with incomes less than \$100,000, and Panel (b) is restricted to the families in which husband-to-wife income ratio is less than 10. For estimating distributions, the whole sample is used. As Panel (a) shows, high-skilled females enjoy a higher wage on average, but they also face a higher dispersion. For the partner's type, it is clear that the positive assortative matching exists, though an evident distinction is not observed here.

The remaining parameters are jointly calibrated from the model, targeting skill-group specific marital shares, fertility rates, and human capital growth rates. For the human capital growth rate, I first get the average years of schooling for the two skill groups in each year, and I calculate the annual growth rate. Then I average the growth rates across the

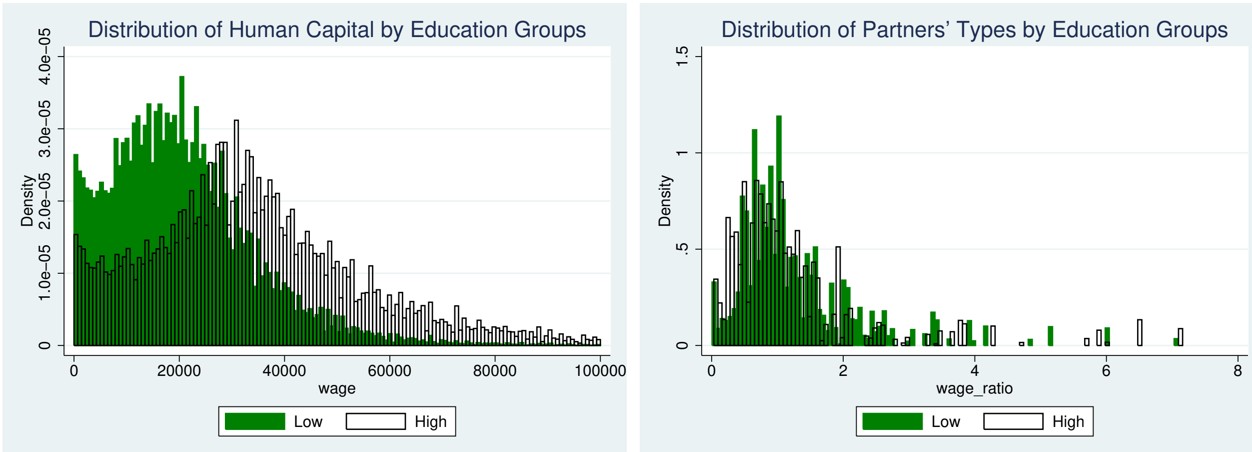
related to lawn, garden, and houseplants, (6) household activities related to animals and pets, (7) household activities related to vehicles, (8) household activities related to appliances, tools, and toys, and (9) household management.

data periods. The value of the high skill group is 1.000482279, and it is 1.001031772 for the low-skilled group. The third step is to take these two numbers to the power of 25 to get the human capital growth rates between two generations. Notice here the growth rate is higher for the low-skilled group, and partly it is because I use years of schooling as the measure of human capital. If instead I use wage data to capture human capital, the growth rate is expected to be higher for the high-skilled group.

Table 1.6: Calibration parameters

| Parameters | Values | Description | Source/Target |
|---|---|---|---|
| $\sigma_c$ | 0.6000 | Intertemporal preference (private consumption) | Assumption |
| $\sigma_X$ | 0.6667 | Intertemporal preference (public good) | Assumption |
| $\sigma_n$ | 0.7500 | Intertemporal preference (children) | Assumption |
| $\gamma$ | 0.6000 | Fertility discounting factor | Assumption |
| $\rho^c$ | 0.5000 | Elasticity of substitution for public good (cohabited) | Assumption |
| $\rho^m$ | 0.5000 | Elasticity of substitution for public good (married) | Assumption |
| $\tau$ | 0.200 | Intergeneration human capital transmission | La Croix and Doepke (2003) |
| $\eta$ | 0.620 | Parents' investment in human capital transmission | La Croix and Doepke (2003) |
| $\pi_0^H$ | 825.2445 | Childrearing resource cost | CRC |
| $\pi_0^L$ | 492.6095 | Childrearing resource cost | CRC |
| $\overline{s_{man}^c}$ | 0.4595 | Husband income contribution (cohabited) | Time Use Survey |
| $\overline{s_{man}^m}$ | 0.4595 | Husband income contribution (married) | Time Use Survey |
| $W_H/W_L$ | 1.6260 | Skill premium | CPS(Pooling) |
| $\underline{X}$ | 0.300 | Subsistence level of public good | CRC |
| $h^H$ | (1.04, 9.78) | Human capital distribution: log normal($\mu$,$\sigma$) | CPS(Pooling) |
| $h^L$ | (0.94, 9.64) | Human capital distribution: log normal($\mu$,$\sigma$) | CPS(Pooling) |
| $\theta_H$ | (0.81, 1.25) | Husband income distribution: log normal($\mu$,$\sigma$) | CPS(Pooling) |
| $\theta_L$ | (0.84, 1.15) | Husband income distribution: log normal($\mu$,$\sigma$) | CPS(Pooling) |
| $B^H$ | 1760 | Human Capital Accumulation | Joint Targets |
| $B^L$ | 1505 | Human Capital Accumulation | Joint Targets |
| $\kappa^s$ | 0.5500 | Return of investment in children's human capital (single) | Joint Targets |
| $\kappa^c$ | 0.8600 | Return of investment in children's human capital (cohabiting) | Joint Targets |
| $\kappa^m$ | 0.8800 | Return of investment in children's human capital (married) | Joint Targets |
| $\alpha_n^s$ | 0.6500 | Utility parameter for kids (single) | Joint Targets |
| $\alpha_n^c$ | 1.3400 | Utility parameter for kids (cohabiting) | Joint Targets |
| $\alpha_n^m$ | 1.3500 | Utility parameter for kids (married) | Joint Targets |
| $\alpha_X$ | 1.1500 | Utility parameter for public good | Joint Targets |
| $\delta_n^s$ | 8 | Fertility premium (single) | Joint Targets |
| $\delta_n^s$ | 10 | Fertility premium (cohabiting) | Joint Targets |
| $\delta_n^m$ | 10 | Fertility premium (married) | Joint Targets |
| $\delta^c$ | 0.2350 | Cohabitation premium | Joint Targets |
| $\delta^m$ | 0.9000 | Marriage premium | Joint Targets |
| $\pi_q^s$ | 0.0240 | Time cost investing in children human capital | Joint Targets |
| $\pi_q^c$ | 0.0220 | Time cost investing in children human capital | Joint Targets |
| $\pi_q^m$ | 0.0170 | Time cost investing in children human capital | Joint Targets |
| $\pi_n^H$ | 0.1967 | Time cost investing in children | Joint Targets |
| $\pi_n^L$ | 0.1865 | Time cost investing in children | Joint Targets |

Figure 1.7: Distributions of $h$ and $\theta$ by Education Groups




(a) human capital $h$ (b) partners' types $\theta$

The calibration results are reported in table 1.7. The targets include marital shares, fertility rates and human capital growth rates for the two skill groups. The model fits the targets quite well: not only the levels but also the differences between two skill groups. This can be seen from the last two rows that all the signs are consistent with the data. Compared to the low-skill group, skilled females are more likely to get married and less likely to cohabit with a partner.

Table 1.7: Calibration Target: Marital Shares (Percent), Fertility, and Human Capital Growth Rate for Two Skill Groups

| | Single | Cohabiting | Married | Fertility | HC Growth |
|---|---|---|---|---|---|
| H-Model | 13.0800 | 2.6400 | 84.2800 | 2.4659 | 1.0157 |
| H-Data | 12.7239 | 2.9099 | 84.3662 | 2.2090 | 1.0121 |
| L-Model | 9.1600 | 8.5200 | 82.3200 | 2.8378 | 1.0276 |
| L-Data | 12.1059 | 5.0680 | 82.8261 | 2.3220 | 1.0261 |
| Diff-Model | 3.9200 | -5.8800 | 1.9600 | -0.3719 | -0.0119 |
| Diff-Data | 0.6180 | -2.1581 | 1.5401 | -0.1130 | -0.0140 |

## 1.5 Basic Results

Based on the model parameterization discussed in the previous section, I now illustrate the performance of the benchmark model. The model gives two groups of predictions that we can observe in the data: Table 1.8 reports marital-group fertility rates, and Table 1.9 reports the ratio of contribution to public good between partners within a household. Conditional on having at least one child, women are predicted to have the highest fertility rate in the marriage group, then women in the cohabitation group, and single females have the lowest fertility rate, which is aligned with what is observed in the data. The model also does a fairly good job of predicting between-group fertility differences in that in general, females in the low-skilled group are more likely to have more children than those with more years of schooling, which is consistent with quantity-quality trade-off theory. Additionally, such a between-group fertility difference is most evident for cohabiting females. The predicted differential fertility rate between unskilled females and skilled females is 0.4075 for those engaging in cohabitation relationships; the counterpart in data is 0.3360.

Table 1.8: Predicted Marital-Group Fertility for Females

| | Single | Cohabiting | Married |
|---|---|---|---|
| H-Model | 1.8307 | 1.8567 | 2.6303 |
| H-Data | 1.8545 | 1.9391 | 2.2217 |
| L-Model | 2.0778 | 2.2643 | 3.0450 |
| L-Data | 2.1252 | 2.2752 | 2.3394 |
| Diff-Model | -0.2472 | -0.4075 | -0.4147 |
| Diff-Data | -0.2706 | -0.3360 | -0.1176 |

Although contribution to public good is not directly observed, I use the reported time allocated to household activities from the Time Use Survey as the data counterpart. The model predicted ratio of time allocated to public good production between two skill groups is 1.0648, which is close to its data counterpart of 1.0213.

Table 1.9: Predicted Contribution to Public Good Production ($s$)

| | High Group | Low Group | Ratio |
|---|---|---|---|
| Model | 0.5747 | 0.5397 | 1.0648 |
| Data | 113.1577 | 110.7969 | 1.0213 |

Note: data report the minutes females denoted to household activities per day

Overall, the benchmark model does a good job predicting fertility rates and between-group fertility differentials. However, a few issues need to be discussed. First, the static framework does not feature any dynamics, and hence, I am not able to say anything about divorce or breakup. Instead, the focus of this paper is to study fertility decisions for females with different skills in various marital statuses. However, utility premium/loss parameters $\delta^c$ and $\delta^m$ capture some flavor of costs associated with cohabitation and marriage such as wedding cost, divorce cost or reputation cost. The calibrated positive values imply that the overall benefit outweighs the cost in cohabitation and marriage relationships. Second, one limitation is that there are only female agents in the model. Missing males makes it hard to clear the marriage market and labor market. It would be become very complicated to include the endogenous marriage matching market in such a macro-setup model. Another reason I do not consider matching process or dynamic transitions is that CPS is a cross-sectional database, so I cannot track individuals over their life-cycles, and hence, there is no information on their previous marital status or fertility decisions.

## 1.6 Counterfactual Experiments

For counterfactual exercises, I conduct two sets of experiments. For the first set, I study the effects of both skill-group specific parameters and marital-group specific ones. Next, I examine dynamics by dividing the sample period into two sub-periods and recalibrate the model. The first sub-period refers to year 1995 to year 2002, and the second sub-period refers year 2003 to year 2008. The targets are skill-group specific marital shares, fertility rate, and human capital growth rate. As discussed, to calculate human capital growth rate, I use years of schooling as the measure instead of wage rates.

### 1.6.1 Counterfactual Exercises

In this section, five groups of key parameters are studied to understand the driving forces behind differential marital decisions and fertility choices, including skill premium, childrearing costs, return of investment in children, partner's commitment, and cohabitation preferences. For each experiment, I present the table with the results on marital shares, total fertility rate, human capital growth rate, and marital-group specific fertility rates. The uparrow ($\uparrow$) and downarrow ($\downarrow$) imply the parameter increases or decreases to a certain value. It is essential to understand how income effect, substitution effect, quality and quantity trade-off, and compositional effect take place together to shape marital decisions and fertility choices for agents from two skill groups differently[15].

#### Wage and Skill Premium

Panel (a) in Table 1.10 reports the result if I decrease the unit wage rate for the skilled to be the same as that of the unskilled, and Panel (b) shows the reverse. Since the wage rate for the unskilled is normalized to be 1 in the benchmark model, this exercise also demonstrates the effect of the skill premium channel. As the wage rate for high-skilled group decreases, the income effect leads them to have fewer children, and such weaker fertility desire shifts people from marriage to being single or engaging in cohabitation relationships. The same story holds for the unskilled when they face a higher wage. Then, they increase the number

[15] Table 1.22 summarizes the results from all counterfactual experiments.

of children, and more females prefer marriage to being single or cohabitation.

Table 1.10: Counterfactual Experiment 1: Wage and Skill Premium

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.5288 | 6.7695 | 82.7017 | 2.6501 | 1.0465 | 1.8983 | 2.0840 | 2.8515 |
| High | 13.3200 | 3.2000 | 83.4800 | 2.2674 | 1.0852 | 1.5321 | 1.7164 | 2.4568 |
| Low | 9.1600 | 8.5200 | 82.3200 | 2.8378 | 1.0276 | 2.0778 | 2.2643 | 3.0450 |
| Diff | 4.1600 | -5.3200 | 1.1600 | -0.5705 | 0.0576 | -0.5458 | -0.5479 | -0.5881 |
| Diff wrt model (High) | 0.2400 | 0.5600 | **-0.8000** | **-0.1985** | 0.0695 | -0.2986 | -0.1404 | -0.1735 |
| Diff wrt model (Low) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

(a) $\omega_H \downarrow = \omega_L$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.2351 | 5.2970 | 84.4679 | 2.8246 | 0.9993 | 2.2067 | 1.9456 | 3.0192 |
| High | 13.0800 | 2.6400 | 84.2800 | 2.4659 | 1.0157 | 1.8307 | 1.8567 | 2.6303 |
| Low | 8.8400 | 6.6000 | 84.5600 | 3.0005 | 0.9913 | 2.3911 | 1.9891 | 3.2099 |
| Diff | 4.2400 | -3.9600 | -0.2800 | -0.5346 | 0.0244 | -0.5605 | -0.1324 | -0.5796 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Diff wrt model (Low) | -0.3200 | -1.9200 | **2.2400** | **0.1626** | -0.0363 | 0.3133 | -0.2752 | 0.1649 |

(b) $\omega_L \uparrow = \omega_H$

### Childrearing Cost

Tables report the results of counterfactual experiments on childrearing costs, including the effort cost associated with educating children (quality) and the time and resource costs of childrearing (quantity). Table 1.11 tells the effects from equating effort cost of educating children for females in cohabitation and marriage status, and it is interesting to see how different tensions play in these two experiments. A lower effort cost would have two opposing effects on fertility rates: the quantity-quality trade-off channel leads to more effort invested in human capital and less in the number of children, while income effect leads to a rise in the fertility rate. When effort cost for females in cohabitation status is reduced to be the same as that faced by married females, cohabitation becomes more attractive, and hence, there is an increase in the cohabitation share. Second, it becomes cheaper to invest in the quality of children rather than the quantity, and hence, the fertility rates for cohabiting females drop for the two skill groups. The same pattern holds when effort cost faced by married females is raised to be the same as that in cohabitation status; then, an increase in marriage is observed. However, in this experiment, the income effect dominates the substitution effect for the skilled, while it is the other way around for the unskilled, which explains why the fertility rate drops for the skilled but increases for the unskilled.

Table 1.11: Counterfactual Experiment 2.1: Effort Cost of Childrearing

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.5172 | 8.6998 | 80.7830 | 2.6534 | 1.0473 | 2.0003 | 1.7271 | 2.9085 |
| High | 13.0400 | 3.5200 | 83.4400 | 2.4416 | 1.0225 | 1.8285 | 1.4785 | 2.6303 |
| Low | 9.2800 | 11.2400 | 79.4800 | 2.7573 | 1.0595 | 2.0845 | 1.8491 | 3.0450 |
| Diff | 3.7600 | -7.7200 | 3.9600 | -0.3158 | -0.0370 | -0.2561 | -0.3706 | -0.4147 |
| Diff wrt model (High) | -0.0400 | **0.8800** | -0.8400 | -0.0243 | 0.0068 | -0.0022 | **-0.3783** | 0.0000 |
| Diff wrt model (Low) | 0.1200 | **2.7200** | -2.8400 | -0.0805 | 0.0319 | 0.0067 | **-0.4152** | 0.0000 |

(a) $\pi_q^c \downarrow = \pi_q^m$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.6103 | 7.5995 | 81.7902 | 2.0269 | 5.6976 | 2.0043 | 1.7851 | 2.0905 |
| High | 13.1600 | 3.5200 | 83.3200 | 0.3478 | 15.4505 | 1.8330 | 1.1237 | 0.0397 |
| Low | 9.3600 | 9.6000 | 81.0400 | 2.8503 | 0.9149 | 2.0883 | 2.1094 | 3.0962 |
| Diff | 3.8000 | -6.0800 | 2.2800 | -2.5024 | 14.5356 | -0.2553 | -0.9858 | -3.0565 |
| Diff wrt model (High) | 0.0800 | 0.8800 | **-0.9600** | -2.1181 | 14.4348 | 0.0023 | -0.7330 | **-2.5907** |
| Diff wrt model (Low) | 0.2000 | 1.0800 | **-1.2800** | 0.0124 | -0.1127 | 0.0104 | -0.1548 | **0.0512** |

(b) $\pi_q^m \uparrow = \pi_q^c$

In the experiment shown by Table 1.12, I change the time cost of childrearing ($\pi_n$) for the two skill groups separately. Thus, a lower (higher) cost leads to higher (lower) fertility rates. Another important matter to notice is the selection effect for the married females. In Panel (a), although there is a decrease in the marriage share, the fertility rate for married females increases, which implies that only females with strong fertility motives will stay in marriages.

Table 1.12: Counterfactual Experiment 2.2: Time Cost of Childrearing

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3972 | 6.9669 | 82.6359 | 2.7490 | 1.0156 | 2.0262 | 2.1000 | 2.9493 |
| High | 12.9200 | 3.8000 | 83.2800 | 2.5679 | 0.9912 | 1.9210 | 1.7651 | 2.7543 |
| Low | 9.1600 | 8.5200 | 82.3200 | 2.8378 | 1.0276 | 2.0778 | 2.2643 | 3.0450 |
| Diff | 3.7600 | -4.7200 | 0.9600 | -0.2699 | -0.0364 | -0.1568 | -0.4991 | -0.2907 |
| Diff wrt model (High) | -0.1600 | 1.1600 | **-1.0000** | **0.1020** | -0.0245 | 0.0903 | -0.0916 | **0.1240** |
| Diff wrt model (Low) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

(a) $\pi_n^H \downarrow= \pi_n^L$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.4498 | 6.0485 | 83.5017 | 2.6256 | 1.0394 | 1.9340 | 2.0588 | 2.8051 |
| High | 13.0800 | 2.6400 | 84.2800 | 2.4659 | 1.0157 | 1.8307 | 1.8567 | 2.6303 |
| Low | 9.1600 | 7.7200 | 83.1200 | 2.7039 | 1.0510 | 1.9847 | 2.1579 | 2.8909 |
| Diff | 3.9200 | -5.0800 | 1.1600 | -0.2380 | -0.0353 | -0.1540 | -0.3011 | -0.2606 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Diff wrt model (Low) | 0.0000 | -0.8000 | 0.8000 | **-0.1339** | 0.0235 | -0.0932 | -0.1064 | -0.1541 |

(b) $\pi_n^L \uparrow= \pi_n^H$

Similar to the previous experiment, Table 1.13 shows that as the resource cost drops (rises) for the skilled (unskilled), the fertility rate increases (decreases) due to income effect. Since overall it becomes less pricy to raise a kid, relatively speaking, marriage becomes less attractive, which explains the decreasing marriage share in Panel (a). The same reasoning holds for Panel (b).

Table 1.13: Counterfactual Experiment 2.3: Resource Cost of Childrearing

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.4893 | 7.9541 | 81.5566 | 2.8473 | 0.9914 | 2.1626 | 2.1971 | 3.0615 |
| High | 13.2000 | 6.8000 | 80.0000 | 2.8666 | 0.9178 | 2.3355 | 2.0601 | 3.0952 |
| Low | 9.1600 | 8.5200 | 82.3200 | 2.8378 | 1.0276 | 2.0778 | 2.2643 | 3.0450 |
| Diff | 4.0400 | -1.7200 | -2.3200 | 0.0287 | -0.1098 | 0.2577 | -0.2042 | 0.0503 |
| Diff wrt model (High) | 0.1200 | 4.1600 | **-4.2800** | **0.4007** | -0.0979 | 0.5048 | 0.2033 | 0.4649 |
| Diff wrt model (Low) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

(a) $\pi_0^H \downarrow= \pi_0^L$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.1546 | 3.9819 | 85.8635 | 2.3836 | 1.1188 | 1.5895 | 1.9944 | 2.5295 |
| High | 13.0800 | 2.6400 | 84.2800 | 2.4659 | 1.0157 | 1.8307 | 1.8567 | 2.6303 |
| Low | 8.7200 | 4.6400 | 86.6400 | 2.3433 | 1.1694 | 1.4712 | 2.0619 | 2.4800 |
| Diff | 4.3600 | -2.0000 | -2.3600 | 0.1226 | -0.1537 | 0.3594 | -0.2052 | 0.1503 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Diff wrt model (Low) | -0.4400 | -3.8800 | **4.3200** | **-0.4945** | 0.1418 | -0.6066 | -0.2024 | -0.5649 |

(b) $\pi_0^L \uparrow= \pi_0^H$

### Return of investment in Children

Both $\kappa$ and $B$ determine the human capital accumulation process of children given parents' human capital and effort invested; Table 1.14 and Table 1.15 illustrate the results, respectively. Similar to the analysis for childrearing cost associated with children's human capital, changes in return of investment in children would have two potential opposing effects on fertility rate depending on whether income effect dominates or substitution effect dominates.

In the top panel in Table 1.14, as the benefit of investing effort in improving human capital for children rises for females in cohabitation status, the high-skilled cohabiting agents choose to have more children and invest less because of the rising benefit. However, for the unskilled, the substitution effect plays such an influential role that they decide to have fewer children.

It is also interesting to see that in the bottom panel, the drop in $\kappa^m$ is so significant that agents from two skill groups experience a decrease in fertility rate due to the lower return.

Table 1.14: Counterfactual Experiment 3.1: Return of Effort Invested in Children

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.5572 | 7.5514 | 81.8914 | 2.6773 | 1.0288 | 2.0018 | 1.9005 | 2.9085 |
| High | 13.0800 | 2.6400 | 84.2800 | 2.4665 | 1.0156 | 1.8307 | 1.8735 | 2.6303 |
| Low | 9.3200 | 9.9600 | 80.7200 | 2.7808 | 1.0352 | 2.0857 | 1.9137 | 3.0450 |
| Diff | 3.7600 | -7.3200 | 3.5600 | -0.3143 | -0.0196 | -0.2550 | -0.0402 | -0.4147 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0006 | **-0.0001** | 0.0000 | **0.0168** | 0.0000 |
| Diff wrt model (Low) | 0.1600 | 1.4400 | -1.6000 | -0.0571 | **0.0077** | 0.0078 | **-0.3505** | 0.0000 |

(a) $\kappa^c \uparrow = \kappa^m$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.4498 | 6.5453 | 83.0049 | 2.7129 | 1.0227 | 1.9965 | 2.1360 | 2.9047 |
| High | 13.0800 | 2.6000 | 84.3200 | 2.4621 | 1.0147 | 1.8307 | 1.8724 | 2.6243 |
| Low | 9.1600 | 8.4800 | 82.3600 | 2.8359 | 1.0267 | 2.0778 | 2.2653 | 3.0422 |
| Diff | 3.9200 | -5.8800 | 1.9600 | -0.3738 | -0.0120 | -0.2472 | -0.3928 | -0.4179 |
| Diff wrt model (High) | 0.0000 | -0.0400 | 0.0400 | -0.0038 | **-0.0010** | 0.0000 | 0.0157 | **-0.0060** |
| Diff wrt model (Low) | 0.0000 | -0.0400 | 0.0400 | -0.0019 | **-0.0009** | 0.0000 | 0.0010 | **-0.0028** |

(b) $\kappa^m \downarrow = \kappa^c$

Compared to $\kappa$ that is closely related to effort invested, $B$ captures the total return of investment in children in which not only effort from parents matter, but also the parents' own human capital levels matter. When the overall human capital accumulation process becomes less efficient for the high-skilled group, agents shift from investing in children's quality to quantity, and such a quality-quantity trade-off leads to a rise in the fertility rate along with a drop in human capital growth rate. Moreover, because of the lower return from children, the additional childrearing-related benefits from marriage turn out to be more attractive for females who want to have a child, which explains the rise in marriage share. The same story holds for the second experiment, in which the total return from investing in children's human capital increases for the unskilled.

Table 1.15: Counterfactual Experiment 3.2: Total Return of Investment in Children

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.4235 | 6.3352 | 83.2413 | 2.7178 | 0.9715 | 1.9821 | 1.8709 | 2.9207 |
| High | 13.0000 | 1.8800 | 85.1200 | 2.4730 | 0.8572 | 1.7869 | 1.0687 | 2.6672 |
| Low | 9.1600 | 8.5200 | 82.3200 | 2.8378 | 1.0276 | 2.0778 | 2.2643 | 3.0450 |
| Diff | 3.8400 | -6.6400 | 2.8000 | -0.3649 | -0.1704 | -0.2910 | -1.1955 | -0.3778 |
| Diff wrt model (High) | -0.0800 | -0.7600 | **0.8400** | **0.0071** | **-0.1585** | -0.0438 | -0.7880 | 0.0369 |
| Diff wrt model (Low) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

(a) $B^H \downarrow= B^L$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.6914 | 6.8000 | 82.5087 | 2.6759 | 1.1589 | 2.0287 | 1.8937 | 2.8915 |
| High | 13.0800 | 2.6400 | 84.2800 | 2.4659 | 1.0157 | 1.8307 | 1.8567 | 2.6303 |
| Low | 9.5200 | 8.8400 | 81.6400 | 2.7789 | 1.2291 | 2.1258 | 1.9118 | 3.0196 |
| Diff | 3.5600 | -6.2000 | 2.6400 | -0.3130 | -0.2134 | -0.2952 | -0.0551 | -0.3893 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Diff wrt model (Low) | 0.3600 | 0.3200 | **-0.6800** | **-0.0589** | **0.2015** | 0.0480 | -0.3525 | -0.0254 |

(b) $B^L \uparrow= B^H$

### Commitment of Partner

Recall that from the calibration section, the ratio of fraction contributed to public good production is measured by the ratio of the time devoted to household activities using data from the U.S. Time Use Survey between a female and her partner. The data show $\overline{s^c_{man}} = 0.5901$ and $\overline{s^m_{man}} = 0.4595$. Such a fraction of time also captures the commitment level of partners. Table 1.16 summarizes the effects. Setting $\overline{s^c_{man}} = \overline{s^m_{man}}$ means the commitment level of partners decreases for cohabiting females, and it follows that the share of females and fertility rate in cohabitation status drop for both skill groups. However, the reason why the overall fertility rates increase for the two skill groups is compositional change. Because on average women in marriage tend to have a larger number of children than females in the other two marital groups, it is natural to observe a rising overall fertility rate because the effect of the decrease in fertility rate for cohabiting females is completely offset by the increase in marriage share. When commitment from partners for married females increases, marriage becomes more attractive, and hence, females deviate from singlehood and cohabitation to marriage for both higher value of public good consumption and higher utility from childrearing activities. However, we see a drop in the fertility rate for unskilled married females due to a trade-off between quantity versus quality of children and trade-off between utility from children versus public good consumption.

Table 1.16: Counterfactual Experiment 4: Commitment of Partner

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.6362 | 2.8165 | 86.5474 | 2.7412 | 1.0494 | 1.9997 | 1.8901 | 2.9085 |
| High | 13.3200 | 0.2400 | 86.4400 | 2.4825 | 1.0278 | 1.8349 | 1.2873 | 2.6303 |
| Low | 9.3200 | 4.0800 | 86.6000 | 2.8680 | 1.0600 | 2.0806 | 2.1857 | 3.0450 |
| Diff | 4.0000 | -3.8400 | -0.1600 | -0.3855 | -0.0322 | -0.2457 | -0.8984 | -0.4147 |
| Diff wrt model (High) | 0.2400 | **-2.4000** | **2.1600** | **0.0166** | 0.0121 | 0.0042 | **-0.5695** | 0.0000 |
| Diff wrt model (Low) | 0.1600 | **-4.4400** | **4.2800** | **0.0302** | 0.0325 | 0.0027 | **-0.0786** | 0.0000 |

(a) $s^c \downarrow = s^m$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 8.8377 | 3.1512 | 88.0111 | 2.6797 | 1.0634 | 1.9676 | 2.1317 | 2.7949 |
| High | 11.2800 | 0.3600 | 88.3600 | 2.5338 | 1.0241 | 1.8050 | 1.5774 | 2.6698 |
| Low | 7.6400 | 4.5200 | 87.8400 | 2.7512 | 1.0826 | 2.0474 | 2.4035 | 2.8562 |
| Diff | 3.6400 | -4.1600 | 0.5200 | -0.2174 | -0.0585 | -0.2424 | -0.8261 | -0.1864 |
| Diff wrt model (High) | -1.8000 | -2.2800 | **4.0800** | 0.0679 | 0.0085 | -0.0257 | -0.2793 | **0.0395** |
| Diff wrt model (Low) | -1.5200 | -4.0000 | **5.5200** | -0.0867 | 0.0551 | -0.0305 | 0.1393 | **-0.1888** |

(b) $s^m \uparrow = s^c$

### Cohabitation and Marriage Preference

In this section, I examine the effects from preference toward cohabitation versus marriage: Table 1.17 reports the results from changing direct premium parameters, and Table 1.18

shows the results from changing fertility preference.

Direct cohabitation and marriage premium play an important role in shaping marital decisions, as can be seen from the large magnitude changes of shares in Experiment 5.1. In the two panels, if there is no extra utility premium associated with marriage, agents retreat from marriage and shift into cohabitation, but the difference between two experiments is the extra utility premium relative to singlehood status. This explains why in Panel (a) single share decreases, while in Panel (b), single share rises. The tensions behind the overall fertility rates are also different. In Panel (a), the drop in the rate of fertility in singlehood is dominated by the increase of fertility rate in cohabitation. Nevertheless, in Panel (b), the increase in the share of singlehood and cohabitation together with the rise of fertility rates in these two groups outweigh the decreasing marriage share.

Table 1.17: Counterfactual Experiment 5.1: Direct Cohabitation and Marriage Premium

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 8.9045 | 75.6854 | 15.4100 | 2.8192 | 0.9102 | 1.9703 | 2.9811 | 2.8139 |
| High | 11.3200 | 76.9200 | 11.7600 | 2.5590 | 0.8698 | 1.8061 | 2.6191 | 2.9914 |
| Low | 7.7200 | 75.0800 | 17.2000 | 2.9469 | 0.9301 | 2.0508 | 3.1585 | 2.7269 |
| Diff | 3.6000 | 1.8400 | -5.4400 | -0.3879 | -0.0603 | -0.2447 | -0.5394 | 0.2645 |
| Diff wrt model (High) | -1.7600 | **74.2800** | -72.5200 | 0.0931 | -0.1459 | -0.0245 | 0.7624 | 0.3610 |
| Diff wrt model (Low) | -1.4400 | **66.5600** | -65.1200 | 0.1090 | -0.0975 | -0.0270 | 0.8943 | -0.3181 |

(a) $\delta^c \uparrow = \delta^m$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 14.9128 | 68.6374 | 16.4498 | 2.7848 | 0.8630 | 2.1200 | 3.0036 | 2.7147 |
| High | 16.0400 | 69.0400 | 14.9200 | 2.5372 | 0.8385 | 1.8898 | 2.6876 | 2.6898 |
| Low | 14.3600 | 68.4400 | 17.2000 | 2.9063 | 0.8750 | 2.2328 | 3.1585 | 2.7269 |
| Diff | 1.6800 | 0.6000 | -2.2800 | -0.3690 | -0.0365 | -0.3430 | -0.4709 | -0.0371 |
| Diff wrt model (High) | 2.9600 | 66.4000 | **-69.3600** | 0.0713 | -0.1772 | 0.0592 | 0.8309 | 0.0595 |
| Diff wrt model (Low) | 5.2000 | 59.9200 | **-65.1200** | 0.0684 | -0.1526 | 0.1550 | 0.8943 | -0.3181 |

(b) $\delta^m \downarrow = \delta^c$

Lastly, I want to study the role of fertility preference. Notice that when the value of preference parameter $\alpha_n$ changes, agents would re-evaluate the value from childrearing activities, which is comprised of utility from quantity of children and quality; therefore, its effect on fertility rate is ambiguous. In the top panel, when agents engaging in cohabitation relationship are assumed to value children as much as those in marriage, they would choose to have more children. The difference between skill groups is that part of the high-skilled females would shift out of marriage to cohabitation, while some low-skilled females would shift out of cohabitation to singlehood. Such compositional change explains the opposing directions of the changes in the overall fertility rates in the first experiment. For the skilled, the decrease in marriage share dominates the increase in fertility rate in the cohabitation group, while for the unskilled, the increase in fertility rates in both singlehood and cohabitation groups dominates the decrease in cohabitation share. In the bottom panel, if preference toward fertility for the married agents is reduced to be the same as that for cohabiting agents, females in the two skill groups experience a retreat from marriage and an increase in fertility rate for married women, which corresponds to a strong selection effect that only those who strongly desire children would remain in marriage status.

Table 1.18: Counterfactual Experiment 5.2: Cohabitation and Marriage Fertility Preference

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.5035 | 6.6237 | 82.8728 | 2.7217 | 1.0204 | 1.9972 | 2.2001 | 2.9085 |
| High | 13.0800 | 2.9200 | 84.0000 | 2.4650 | 1.0140 | 1.8307 | 1.8914 | 2.6303 |
| Low | 9.2400 | 8.4400 | 82.3200 | 2.8476 | 1.0236 | 2.0788 | 2.3516 | 3.0450 |
| Diff | 3.8400 | -5.5200 | 1.6800 | -0.3826 | -0.0096 | -0.2482 | -0.4602 | -0.4147 |
| Diff wrt model (High) | 0.0000 | 0.2800 | -0.2800 | **-0.0009** | -0.0017 | 0.0000 | **0.0347** | 0.0000 |
| Diff wrt model (Low) | 0.0800 | -0.0800 | 0.0000 | **0.0098** | -0.0040 | 0.0010 | **0.0873** | 0.0000 |

(a) $\alpha_n^c \uparrow = \alpha_n^m$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3430 | 8.1656 | 81.4914 | 2.6965 | 1.0205 | 1.9923 | 1.9673 | 2.9259 |
| High | 13.0000 | 3.1200 | 83.8800 | 2.4666 | 1.0217 | 1.8282 | 1.7511 | 2.6455 |
| Low | 9.0400 | 10.6400 | 80.3200 | 2.8093 | 1.0200 | 2.0728 | 2.0732 | 3.0633 |
| Diff | 3.9600 | -7.5200 | 3.5600 | -0.3427 | 0.0018 | -0.2445 | -0.3221 | -0.4178 |
| Diff wrt model (High) | -0.0800 | 0.4800 | **-0.4000** | 0.0007 | 0.0060 | -0.0024 | -0.1056 | **0.0152** |
| Diff wrt model (Low) | -0.1200 | 2.1200 | **-2.0000** | -0.0285 | -0.0076 | -0.0051 | -0.1910 | **0.0183** |

(b) $\alpha_n^m \downarrow = \alpha_n^c$

### A Short Summary

In the five groups of counterfactual experiments, we see the tensions between income effect, substitution effect, quantity-quality trade-off, selection effect, and compositional effect for the two skill groups. For example, in Experiment 1, income effect dominates so that increasing wage rate leads to a higher fertility rate. In contrast, in Experiment 2.1, the substitution effect dominates the income effect, and hence when effort cost for married females increases, the unskilled experience an increase in fertility rate. As time cost of childrearing for the skilled decreases in Experiment 2.2, a strong selection effect is observed in which females with strong fertility motives choose stay in marriage. When the commitment level of partners decreases for cohabiting females, as shown in Experiment 4, it is due to the compositional change that the overall fertility rates increase for the two skill groups. Moreover, cohabitation and marriage preference does have an influential role in shaping females' marital decisions, as can be seen from the large magnitude of changes in marital shares. Understanding the relative importance different channels possess is essential to studying the aggregate trends and divergent patterns between the skilled and the unskilled over time, which is the focus of the next section.

### 1.6.2 Dynamics

To understand changes in the trends of marriage, cohabitation, and fertility rate for two skill groups, I consider two regimes. Wage rates, childrearing costs, return of investment in children, partner's commitment, and direct cohabitation premium are assumed to change over time, among which wage ($\omega$), resource cost of childrearing ($\pi_0$), and partner's commitment ($s$) will be directly estimated from data, and the rest of parameters ($B, \kappa, \pi_q, \pi_n, \delta^c$) will be backed out by calibrating the model for two sub-periods[16].

In the first regime, consistent with data, high-skilled agents are more likely to choose singlehood and less likely to choose cohabitation or marriage than low-skilled agents; however, in the second regime, more high-skilled female agents choose marriage, which is aligned with data observations. Between the two regimes, the model predicts that females in both skill groups experience a drop in marriage and rate of fertility, accompanied by an increase in cohabitation, which is consistent with data. The only exception that the model fails to target is that the model-generated single rate decreases for both skill groups, but in the data, more low-skilled females actually have chosen singlehood. The model predicts a drop in fertility rate for females in all marital groups. However, one issue to point out is that the high-skilled married females actually have experienced a rise in fertility, although the

[16] Table 1.23 summarizes the newly recalibrated parameters for the two sub-periods. Table 1.24 and Table 1.25 show the targets and model performance, respectively. The model is able to capture (1) fertility rates for different marital status in two sub-periods and (2) the changes of both marital shares and fertility rates for the two skill groups over time.

0.0079 increase is not significant. For between-skill-group differentials, both the singlehood and cohabitation gaps have narrowed, while the marriage gap has expanded. The fertility gap also has shrunk.

For counterfactual experiments, I restore the value of parameters of interest in the second sub-period to be the same as the value in the first period to study the dynamics. Experiment 1 refers to wage and skill premium channel by changing the value of wage rates (↑) for the two skill groups; Experiment 2 focuses on childrearing costs, which consist of effort cost (↑), time cost (↑), and resource cost of childrearing (↑); Experiment 3 examines the return of investment in children's human capital (↑); Experiment 4 studies the importance of commitment level of potential partners (↑); and Experiment 5 emphasizes the importance of cohabitation preference (↑)[17].

### Decomposition

Results are summarized in Table 1.19, in which the first row shows the model-predicted change of cohabitation share, marriage share, and fertility rates, and the rest report normalized change and relative contribution for each experiment[18].

[17]See Table 1.26 to Table 1.33 for detailed model predictions of each counterfactual experiment.

[18]Panel (a) and Panel (b) report the results for the two skill groups, and Panel (c) reports the changes of between-skill-group differences. For example, the first row in Panel (c) means that cohabitation share gap between two skill groups drops by 0.0224, marriage gap grows by 0.0232, and fertility gap narrows by 0.3347.

Table 1.19: Dynamics Counterfactual Experiments: Decomposition

| | Cohabitation | | Married | | Fertility | |
|---|---|---|---|---|---|---|
| | change | contribution | change | contribution | change | contribution |
| Model | 0.7600 | | -0.0400 | | -0.5374 | |
| Exp1: skill premium | -0.0385 | -5.06% | 0.0048 | -12.12% | -0.0227 | 4.22% |
| Exp2: childrearing cost | -0.1684 | -22.15% | 0.0246 | -61.62% | -0.4889 | **90.96%** |
| Exp3: return in children | 0.2453 | **32.28%** | -0.0194 | **48.48%** | 0.0317 | -5.89% |
| Exp4: partner's commitment | 0.2646 | **34.81%** | -0.0170 | **42.42%** | -0.0518 | 9.64% |
| Exp5: cohabitation preference | 0.4570 | **60.13%** | -0.0331 | **82.83%** | -0.0057 | 1.07% |
| SUM | | 100% | | 100% | | 100% |

(a) high-skilled group

| | Cohabitation | | Married | | Fertility | |
|---|---|---|---|---|---|---|
| | change | contribution | change | contribution | change | contribution |
| Model | 3.0000 | | -2.3600 | | -0.4628 | |
| Exp1: skill premium | 1.2871 | **42.90%** | -1.0507 | **44.52%** | 0.0075 | -1.63% |
| Exp2: childrearing cost | 0.5903 | 19.68% | -0.3879 | 16.44% | -0.2350 | **50.79%** |
| Exp3: return in children | 1.1419 | **38.06%** | -0.9456 | **40.07%** | -0.1580 | **34.14%** |
| Exp4: partner's commitment | -0.5516 | -18.39% | 0.4688 | -19.86% | -0.0781 | 16.89% |
| Exp5: cohabitation preference | 0.5323 | 17.74% | -0.4445 | 18.84% | 0.0009 | -0.19% |
| SUM | | 100% | | 100% | | 100% |

(b) low-skilled group

| | Cohabitation | | Married | | Fertility | |
|---|---|---|---|---|---|---|
| | change | contribution | change | contribution | change | contribution |
| Model | -2.2400 | | 2.3200 | | -0.3347 | |
| Exp1: skill premium | -2.0779 | **92.76%** | 1.7069 | **73.58%** | -0.0446 | 13.33% |
| Exp2: childrearing cost | -1.4147 | **63.16%** | 1.3103 | **56.48%** | -0.1611 | **48.14%** |
| Exp3: return in children | -0.9874 | **44.08%** | 0.8294 | **35.75%** | -0.0305 | 9.12% |
| Exp4: partner's commitment | 1.6505 | -73.68% | -1.2021 | -51.81% | -0.0819 | **24.47%** |
| Exp5: cohabitation preference | 0.5895 | -26.32% | -0.3246 | -13.99% | -0.0166 | 4.95% |
| SUM | | 100% | | 100% | | 100% |

(c) difference between skill groups

### Discussion

Three important messages are delivered. First, return of investment in children's quality plays an influential role in determining marital and fertility choices. This novel channel explains one-third of the rise in cohabitation and almost half of the drop in marriage for the skilled. For the low-skilled group, changes of return in children explains about 40% of marital changes and 34% of the decrease in the rate of fertility. As documented in the empirical section, high-skilled females not only experience a higher return in children, but also this return increases faster compared to the low-skilled group. Consequently, we observe a negative contribution of return in children to the drop in fertility for the skilled since they would like to have more kids together with a higher investment in children's education. Nevertheless, for the unskilled, the change in return of investment in children is not strong enough to compensate for the influence from the quantity-quality trade-off, and thus they decrease the fertility rate while increasing the investment into children's human capital. Because of this opposing force that the return in children plays on fertility choices for two skill groups, about 9% the shrinking fertility gap could be explained by this channel. For changes in marital shares, different return of investment in children helps explain 44.08% of the narrower gap of cohabitation share and 35.75% of widened gap of marriage share.

Second, it is important to see that the wage channel affects the two skill groups in a different way. In the data, the unit wage rate for the unskilled has increased by 8.29% from 0.9602 to 1.0398, and the wage rate for the skilled rose from 1.6030 to 1.6080 over two sub-periods. For the low education group, income effect on fertility dominates so that they can afford to have more children. At the same time, rising income weakens the gains of marriage from gender specialization. Consistent with the conventional theory, this contributes to 44.52% of the decrease in marriage and 42.90% of the increase in cohabitation. However, for the high education group, higher income implies higher opportunity cost of raising children, thus leading to the positive contribution of 4.22% to the decreasing fertility rate. Meanwhile, a rising wage rate enables the skilled females to enjoy a higher return from the positive assortative matching process. As documented by Greenwood et al. (2014) and Greenwood et al. (2016), there exists a positive assortative matching, and it increases over time in the United States. Because of the rising skill premium, the high-skilled females benefit more from positive assortative matching, and this explains the negative effect that the wage channel contributes to the changes in cohabitation and marriage. Such a novel positive assortative matching effect for the skilled, together with the conventional wage effect for the unskilled, help explain most of the divergence of marital choices between skill groups.

Third, the skilled are more sensitive to increasing commitment from partners and cohabitation preference, while the unskilled are more vulnerable to the rising childrearing costs when making marital decisions. The drop in the rate of fertility for two skill groups can be largely explained by the rising costs of childrearing. In all, 90.96% of the drop in fertility rate for the skilled and over half of the drop for the unskilled can be attributed to the rising childrearing costs. One thing to notice is the different influences that rising childrearing cost has on marital decisions for two skill groups, which mainly comes from effects of rising resource cost[19]. The resource cost ($\pi_0$) calibrated with data show that females in two skill groups have been bearing a higher childrearing cost over time and the increase in the cost is faster for the high-skilled females: the resource cost has increased by 95.96% for the skilled and 74.80% for the unskilled. When the unskilled face a higher resource cost, they deviate from marriage and have fewer kids. However, for the high-skilled group, as overall it becomes more pricy to raise a kid, marriage becomes relatively more attractive because of the additional benefit associated with childrearing activities. The strong selection effect is observed in that a group of females who strongly like kids will choose marriage. This explains the two negative numbers for Experiment 2 in Panel (a). Similar to the wage channel that posits

[19]See Table 1.29 for detailed result.

different effects for the skill groups, rising resource cost plays a crucial role in understanding the divergence. This channel contributes 63.16% of the shrinking cohabitation gap, 56.48% of the widened marriage gap, and 48.14% of the narrower fertility gap.

Partner's commitment ($\overline{s_{man}}$), measured by the fraction of time devoted to household-related activities between partners, increases for both cohabiting and married couples, which contributes 34.81% of the rise in cohabitation and 42.42% of the drop in marriage for the skilled. However, for low-skilled females, this channel plays an insignificant role and works in the opposite direction because of different responses on public good consumption. For example, in the experiment in which the value of commitment for cohabiting agents is restored to the initial value, instead of retreating from cohabitation, low-skilled females shift from marriage to cohabitation, decrease fertility rate, increase the fraction devoted to public good production, and enjoy a higher utility from public good. Due to these opposing forces on two skill groups, a rising partner's commitment explains over one-quarter of the shrinking fertility gap and posits a huge negative effect on marital differentials. Another important factor to understand the rising cohabitation is people's preference. In all, 60.13% of the rise in cohabitation and 82.83% of the drop in marriage can be explained by the increasing cohabitation preference for the skilled; for the unskilled, the effect is less pronounced but still significant. Such rising utility toward cohabitation can be supported by the changes in social norms and people's attitudes toward unmarried couples, and changes in legal treatment in the United States. In a recent survey conducted by the Pew Research Center, Taylor (2010) found that members of the older generation (adults age 65 and older) are critical of unmarried couples, regardless whether they are opposite-sex or same-sex couples, but members of the younger generation (age 18 to 29 years old) are not. In addition to the growing acceptance of unmarried couples living together in society, cohabitants are getting more protection from the legal system. Although to some extent from a legal standpoint cohabitation can be beneficial because unmarried partners are not bound by marriage laws, unmarried partners do not enjoy the same rights that are usually granted to married couples automatically, such as marriage property laws. The law concerning cohabitants' rights varies immensely from state to state in the United States. According to Bowman (2004), a substantial history of attempts by the courts has been observed to protect vulnerable parties in cohabiting relationships. Many states and localities offer variegated bundles of rights to cohabitants. For example, Vermont, Massachusetts, and California have extended all the benefits of marriage under state law to same-sex cohabitants. With more protection extended from traditional marriage to cohabitation, both economic and noneconomic, cohabitation becomes a desirable living arrangement.

### Summary

To summarize, for the skilled, higher implicit return of investment in children's human capital compensates for part of the growing opportunity cost of childrearing, and a significant income effect from positive assortative matching dominates the conventional wage channel. In all, 34.81% of the rise in cohabitation and 42.42% of the drop in marriage for the skilled can be explained by rising return in children, and 38.06% and 40.07%, respectively, for the unskilled. Furthermore, rising childrearing cost plays a significant role in explaining the declining fertility rates. In all, 90.96% of the drop in fertility rate for the skilled and over half of the drop for the unskilled can be attributed to rising childrearing costs. Especially when resource cost increases, a strong selection effect exists so that those high-skilled females with strong fertility motives shift into marriage. Most of the shrinking cohabitation gap and widened marriage gap between the two skill groups can be explained by the rising wage and skill premium, increasing childrearing costs, and growing return in children. Three channels together contribute to around 165.8% of the increasing marriage differentials between skill groups, and a partner's commitment together with cohabitation preference attributes to negative 65.8%.

## 1.7 Robustness Check and Further Discussion

### 1.7.1 Robustness Check

In this section, I perform two sets of robustness checks for the empirical findings on divergent marital decisions between two skill groups. First, I use the full sample without age restriction, and then I discuss issues related to ethnic groups.

Figure 1.15 shows the trends of cohabitation and marriage, and Figure 1.16 shows the trends of unpartnered females if the full sample is used without age restriction. Still, both skill groups have experienced an increase in cohabitation and decrease in marriage, and the change is more dramatic for low-skilled females. However, the trend of singlehood differs between skill groups in that an increasing number of females is currently single, while this share has been decreasing for the skilled. Such a decline in singlehood is driven by the younger high-skilled females, which is not surprising since they have not reached stable relationships yet in their early ages, possibly because of pursuing education or early career planning. Age restriction cannot be relaxed to calculate completed fertility rate because females have not reached their late childrearing years.

Another important issue is different marital and fertility decisions made by various ethnic groups. In the data, around 83.55% of sample identified themselves as "White" and 10.8% as "Black/Negro." Figure 1.17 to Figure 1.21 report trends of marital status and fertility rates for the white females and black females in the sample. The divergence is even more dramatic for the white females. For example, the marriage share for the high-skilled white females is almost flat from the 1980s to the current period, which reinforces the puzzle that standard wage story and gender specialization theory fail to explain. However, for the black females, although it is still true that divergence between marriage holds, the increase in cohabitation is more evident among the high-skilled group. Future work can examine different marital behaviors among various racial groups since cultural norms may be of great importance to understand people's choices on childrearing activities and living arrangements.

### 1.7.2 Marriage Market

The marriage market is exogenous in the way that the positive assortative matching is assumed between the female agent and her partner in this paper, which is governed by the fixed distribution of types of partners ($\theta$). However, there is a debate about how assortative matching changes over time. Several papers in the literature claim that positive assortative matching has been increasing in the United States. For example, Greenwood et al. (2014) and Greenwood et al. (2016) document the rise of positive assortative matching from 1960 to 2005; Schwartz and Mare (2005) record the increase in educational homogamy from 1960 to 2003. Nevertheless, Schwartz and Mare (2005) use both CPS and ACS data to dispute the argument, claiming that the increase of assortative matching and educational homogamy is sensitive to the choice of educational categories. The distribution of $\theta$ is not recalibrated for the dynamics counterfactual experiments because the marriage market is exogenously given and this is not the main focus of this paper, so I want to avoid getting into the debate. Another important future work is to include males in the model and emphasize the matching process for cohabitation and the marriage market, which also requires longitudinal data that transitions among different marital statuses.

## 1.8 Conclusion

This paper documents the puzzle in divergence of marital choices and fertility decision between skill groups in that low-skilled females have experienced a more dramatic drop in marriage and fertility along with a more evident increase in cohabitation compared with high-skilled females, which challenges the conventional wage story and gender specialization theory. I argue that the following channels would help explain this puzzle. For skilled females, higher implicit return of investment in children's human capital compensates for part of the growing opportunity cost of childrearing, a significant income effect from positive assortative matching dominates the conventional wage channel, and when childrearing resource cost increases, a selection effect exists so that those with strong fertility motives shift into marriage.

Building on the trade-off between private consumption, public good consumption, and utility from children, I use the model to quantitatively explore the importance of different channels. Calibrating the benchmark model using targets from 1995 to 2008, I am able to capture both within-group fertility rates and between-group fertility differentials. Counterfactual exercises show that 34.81% of the rise in cohabitation and 42.42% of the drop in marriage for the skilled can be explained by the rising return in children, and 38.06% and 40.07%, respectively, for the unskilled. In addition to return in children, rising childrearing cost plays a significant role in explaining the declining fertility rates. Moreover, high-skilled females are more sensitive to rises in their partners' commitment and cohabitation preference, while low-skilled females are more vulnerable to rises in wage and childrearing cost. Most of the shrinking cohabitation gap and widened marriage gap between the two skill groups can be explained by the rising wage and skill premium, increasing childrearing costs, and growing return in children. This paper has shed light on understanding how income inequality and changes in labor market conditions shape females' decisions about family structures and fertility.

One extension is to study distribution within each skill group instead of only focusing on the average. This would help us better study the role that inequality plays. The top 10 percent of females may behave in a very different way than the bottom 10 percent because of the different opportunity cost they face. The top 0.1 percent may also behave in a distinct way than the top 1 percent since for this group, not only income matters, but also family wealth plays an influential role. In addition, allowing for breakups/divorce, investigating dynamic transitions, and incorporating a matching market with male agents are all areas that I intend to incorporate in future work. In this way, I will be able to take into consideration the changes in the legal system and study how policy changes affect people's marital choices.

## 1.9 Appendix (Not intended for publication)

### 1.9.1 Model Appendix

#### Random draws for potential partners

Recall that the equation 1.4 can be rewritten into:

$$\begin{cases} X_t^c = w_t s_t(1 - \pi_q^c q_t n_t - \pi_n n_t) \cdot [1 + (\theta s_{man}^c)^{\rho^c}]^{\frac{1}{\rho^c}}/\xi \\ X_t^m = w_t s_t(1 - \pi_q^m q_t n_t - \pi_n n_t) \cdot [1 + (\theta s_{man}^m)^{\rho^m}]^{\frac{1}{\rho^m}}/\xi \end{cases}$$

Denote $M = [1 + (\theta s_{man})^\rho]^{\frac{1}{\rho}}$, and I have the followings:

$$\begin{aligned} \frac{\partial M}{\partial \theta} &= s_{man}[1 + (\theta s_{man}]^\rho)^{\frac{1}{\rho}-1}(\theta s_{man})^{\rho-1} > 0 \\ \frac{\partial M}{\partial s_{man}} &= \theta[1 + (\theta s_{man}]^\rho)^{\frac{1}{\rho}-1}(\theta s_{man})^{\rho-1} > 0 \\ \frac{\partial M}{\partial \rho} &= [1 + (\theta s_{man})^\rho]^{\frac{1}{\rho}}[\frac{(\theta s_{man})^\rho ln(\theta s_{man})}{[1 + (\theta s_{man})^\rho]\rho} - \frac{ln(1 + (\theta s_{man})^\rho)}{\rho^2}] < 0 \end{aligned}$$

#### Marital Choices

*1. Single without Kids: S0*

$$U_t(h_t, \mathbb{1}_t^{col}, \theta; S0) = \max_{c_t \geq 0} \quad \frac{{w_t}^{1-\sigma_c}}{1 - \sigma_c}$$

*2. Single with Kids: S1 (omitting the superscript of $\pi_q$)*

$$U_t(h_t, \mathbb{1}_t^{col}, \theta; S1) = \max_{c_t \geq 0, 1 \geq s_t \geq 0, n_t \geq 0, q_t \geq 0, X_t \geq \underline{X}} \frac{\big[w_t(1-s_t)(1-\pi_n n_t - \pi_q q_t n_t) - \pi_0 n_t\big]^{1-\sigma_c}}{1-\sigma_c}$$
$$+ \alpha_n n_t^{\gamma}\Big(\frac{\big[B_t n_t h_t{}^{\tau}(\kappa+q)^{\eta}\big]^{1-\sigma_n}}{1-\sigma_n} + \delta_n\Big)$$

First order conditions wrt. n, q, s are:

$$\frac{w_t(\pi_n + \pi_q q_t) + \pi_0}{\big[w_t(1-s_t)(1-\pi_n n_t - \pi_q q_t n_t) - \pi_0 n_t\big]^{\sigma_c}}$$
$$= \frac{\alpha_n(\gamma+1-\sigma_n)}{1-\sigma_n} \cdot [B_t h_t^{\tau}(\kappa+q_t)^{\eta}]^{(1-\sigma_n)} \cdot n_t^{\gamma-\sigma_n} + \alpha_n \delta_n \gamma \cdot n_t^{\gamma-1}$$
$$\frac{w_t \pi_q n_t}{\big[w_t(1-s_t)(1-\pi_n n_t - \pi_q q_t n_t) - \pi_0 n_t\big]^{\sigma_c}} = \alpha_n \eta \cdot (B_t h_t^{\tau})^{(1-\sigma_n)} \cdot (\kappa+q_t)^{\eta(1-\sigma_n)-1} \cdot n_t^{\gamma+1-\sigma_n}$$

From the FOC wrt $n$ and $q$, we have (omitting subscript $t$ for notation simplification) :

$$\frac{w(\pi_n + \pi_q q) + \pi_0}{w\pi_q n}$$
$$= \frac{\gamma+1-\sigma_n}{\eta(1-\sigma)}\frac{\kappa+q}{n} + \frac{\gamma\delta_n}{\eta}\frac{n^{\sigma_n-2}}{(Bh^{\tau})^{(1-\sigma_n)}(\kappa+q)^{\eta(1-\sigma_n)-1}}$$

Hence we have

$$\frac{w(\pi_n + \pi_q q) + \pi_0}{w\pi_q}$$
$$= \frac{\gamma+1-\sigma_n}{\eta(1-\sigma_n)}(\kappa+q) + \frac{\gamma\delta_n}{\eta}\frac{n^{\sigma_n-1}}{(Bh^{\tau})^{(1-\sigma_n)}(\kappa+q)^{\eta(1-\sigma_n)-1}}$$

Further simplifying algebra leads to the following:

$$\frac{w(\pi_n + \pi_q q) + \pi_0}{w\pi_q}$$
$$= \frac{\gamma+1-\sigma_n}{\eta(1-\sigma_n)}(\kappa+q) + \frac{\gamma\delta_n}{\eta(Bh^{\tau})^{(1-\sigma_n)}}\frac{(\kappa+q)^{1-\eta(1-\sigma_n)}}{n^{1-\sigma_n}}$$

Denote:

$$\bar{A} = w\pi_q \cdot \frac{\gamma + 1 - \sigma_n}{\eta(1-\sigma_n)} - w\pi_q = w\pi_q \frac{\gamma + (1-\sigma_n)(1-\eta)}{\eta(1-\sigma_n)} > 0$$

$$\bar{B} = w\pi_q \cdot \frac{\gamma\delta_n}{\eta(Bh^{\tau})^{(1-\sigma_n)}} > 0$$

$$\bar{D} = w\pi_q \cdot \frac{\kappa(\gamma + 1 - \sigma_n)}{\eta(1-\sigma_n)} - (w\pi_n + \pi_0)$$

$$\bar{A} \cdot q + \bar{B} \cdot \frac{(\kappa + q)^{1-\eta(1-\sigma_n)}}{n^{1-\sigma_n}} + \bar{D} = 0$$

In the case $s = 0$, it is clear to see that:

$$n^{1-\sigma_n} = \frac{\bar{B}(\kappa+q)^{1-\eta(1-\sigma_n)}}{-\bar{D} - \bar{A}q}$$

$$\Rightarrow \frac{\partial n^{1-\sigma_n}}{\partial q} = \bar{B}\frac{[1-\eta(1-\sigma_n)](\kappa+q)^{-\eta(1-\sigma_n)}(-\bar{D}-\bar{A}q) + \bar{A}(\kappa+q)^{1-\eta(1-\sigma_n)}}{(-\bar{D}-\bar{A}q)^2}$$

Hence quantity-quality trade-off holds when: $\dfrac{-\bar{B}}{\bar{D}+\bar{A}q} > 0$

*3. Cohabited or Married without Kids: C0 & M0*

$$U_t(h_t, \mathbb{1}_t^{col}, \theta; C0) = \max_{c_t \geq 0, 1 \geq s_t, X_t \geq \underline{X}} \Big\{ \frac{\big[w_t(1-s_t)\big]^{1-\sigma_c}}{1-\sigma_c} + \alpha_X^c \frac{([(w_t s_t)^{\rho^c} + (w_{man,t} s_{man,t}^c)^{\rho^c}]^{\frac{1}{\rho^c}}/\xi - \underline{X})^{1-\sigma_X}}{1-\sigma_X} \Big\}(1+\delta^c)$$

$$U_t(h_t, \mathbb{1}_t^{col}, \theta; M0) = \max_{c_t \geq 0, 1 \geq s_t, X_t \geq \underline{X}} \Big\{ \frac{\big[w_t(1-s_t)\big]^{1-\sigma_c}}{1-\sigma_c} + \alpha_X^m \frac{([(w_t s_t)^{\rho^m} + (w_{man,t} s_{man,t}^m)^{\rho^m}]^{\frac{1}{\rho^m}}/\xi - \underline{X})^{1-\sigma_X}}{1-\sigma_X} \Big\}(1+\delta^m)$$

First order condition wrt. $s_t$ is:

$$\frac{1}{\big[w_t(1-s_t)\big]^{\sigma_c}} = \frac{\alpha_X}{\xi} \cdot \frac{\big[1 + (\theta s_{man})^{\rho}\big]^{\frac{1}{\rho}}}{\big(w_t s_t [1 + (\theta s_{man})^{\rho}]^{\frac{1}{\rho}}/\xi - \underline{X}\big)^{\sigma_X}}$$

And hence if $\sigma_c = \sigma_X = \sigma$ we can simplify equations further into the following:

$$s_t = \frac{\underline{X} + w_t\Big\{\frac{\alpha_X}{\xi}\cdot\big[1+(\theta s_{man})^\rho\big]^{\frac{1}{\rho}}\Big\}^{\frac{1}{\sigma}}}{w_t[1+(\theta s_{man})^\rho]^{\frac{1}{\rho}}/\xi + w_t\Big\{\frac{\alpha_X}{\xi}\cdot\big[1+(\theta s_{man})^\rho\big]^{\frac{1}{\rho}}\Big\}^{\frac{1}{\sigma}}}$$

*4. Cohabiting or Married with Kids: C1 & M1*

$$\begin{aligned}
U_t(h_t, \mathbb{1}_t^{col}, \theta; C1) = &\max_{c_t\geq 0, 1\geq s_t\geq 0, n_t\geq 0, q_t\geq 0, X_t\geq \underline{X}} \Big\{\frac{\big[w_t(1-s_t)(1-\pi_n n_t - \pi_q q_t n_t) - \pi_0 n_t\big]^{1-\sigma_c}}{1-\sigma_c} \\
&+ \alpha_n^c n_t^\gamma\Big(\frac{\big[n_t {h_t}^\tau(\kappa+q_t)^\eta\big]^{1-\sigma_n}}{1-\sigma_n} + \delta_n\Big) \\
&+ \alpha_X^c \frac{([(w_t s_t(1-\pi_q^c q_t n_t - \pi_n n_t))^{\rho^c} + (w_{man,t}s^c_{man,t})^{\rho^c}]^{\frac{1}{\rho^c}}/\xi - \underline{X})^{1-\sigma_X}}{1-\sigma_X}\Big\}(1+\delta_c)
\end{aligned}$$

$$\begin{aligned}
U_t(h_t, \mathbb{1}_t^{col}, \theta; M1) = &\max_{c_t\geq 0, 1\geq s_t\geq 0, n_t\geq 0, q_t\geq 0, X_t\geq \underline{X}} \Big\{\frac{\big[w_t(1-s_t)(1-\pi_n n_t - \pi_q q_t n_t) - \pi_0 n_t\big]^{1-\sigma_c}}{1-\sigma_c} \\
&+ \alpha_n^m n_t^\gamma\Big(\frac{\big[n_t {h_t}^\tau(\kappa+\mu_m+q_t)^\eta\big]^{1-\sigma_n}}{1-\sigma_n} + \Delta_n\Big) \\
&+ \alpha_X^m \frac{([(w_t s_t(1-\pi_q^m q_t n_t - \pi_n n_t))^{\rho^m} + (w_{man,t}s^m_{man,t})^{\rho^m}]^{\frac{1}{\rho^m}}/\xi - \underline{X})^{1-\sigma_X}}{1-\sigma_X}\Big\}(1+\delta_m)
\end{aligned}$$

First order conditions wrt. n, q, s are:

$$\begin{aligned}
&\frac{w_t(1-s_t)(\pi_n+\pi_q q_t)+\pi_0}{\big[w_t(1-s_t)(1-\pi_n n_t-\pi_q q_t n_t)-\pi_0 n_t\big]^{\sigma_c}} \\
&= \frac{\alpha_n(\gamma+1-\sigma_n)}{1-\sigma_n}\cdot[B_t h_t^\tau(\kappa+q_t)^\eta]^{(1-\sigma_n)}\cdot n_t^{\gamma-\sigma_n} + \alpha_n\delta_n\gamma\cdot n_t^{\gamma-1} \\
&\frac{w_t(1-s_t)\pi_q n_t}{\big[w_t(1-s_t)(1-\pi_n n_t-\pi_q q_t n_t)-\pi_0 n_t\big]^{\sigma_c}} = \alpha_n\eta\cdot(B_t h_t^\tau)^{(1-\sigma_n)}\cdot(\kappa+q_t)^{\eta(1-\sigma_n)-1}\cdot n_t^{\gamma+1-\sigma_n} \\
&\frac{1-\pi_n n_t-\pi_q q_t n_t}{\big[w_t(1-s_t)(1-\pi_n n_t-\pi_q q_t n_t)-\pi_0 n_t\big]^{\sigma_c}} = \frac{\alpha_X}{\xi}\cdot\frac{(1-\pi_n n_t-\pi_q q_t n_t)\big[1+(\theta s_{man})^\rho\big]^{\frac{1}{\rho}}}{\big(w_t s_t[1+(\theta s_{man})^\rho]^{\frac{1}{\rho}}/\xi-\underline{X}\big)^{\sigma_X}}
\end{aligned}$$

And hence if $\sigma_c = \sigma_X = \sigma$ we have the following:

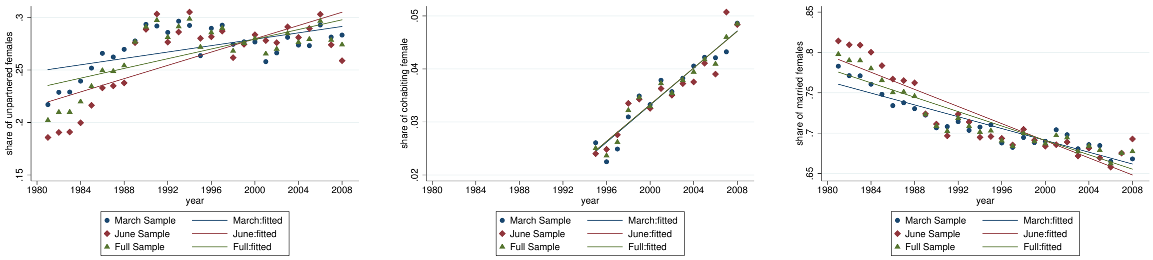
$$s_t = \frac{\underline{X} + \left[w_t(1 - \pi_n n_t - \pi_q q_t n_t) - \pi_0 n_t\right] \left[\frac{\alpha_X}{\xi}[1 + (\theta s_{man})^\rho]^{\frac{1}{\rho}}\right]^{\frac{1}{\sigma}}}{w_t(1 - \pi_n n_t - \pi_q q_t n_t)[1 + (\theta s_{man})^\rho]^{\frac{1}{\rho}}/\xi + \left[w_t(1 - \pi_n n_t - \pi_q q_t n_t)\right] \left[\frac{\alpha_X}{\xi}[1 + (\theta s_{man})^\rho]^{\frac{1}{\rho}}\right]^{\frac{1}{\sigma}}} \tag{1.5}$$

### 1.9.2 Data Appendix

**Comparison using March data, June data, and Full sample**

The Current Population Survey (CPS) is a monthly survey of about 60,000 U.S. households conducted by the United States Census Bureau for the Bureau of Labor Statistics (BLS). Since 1948, the CPS has included supplemental questions (at first, in April; later, in March) on income received in the previous calendar year, which are used to estimate the data on income and work experience. These data are the source of the annual Census Bureau report on income, poverty, and health insurance coverage - CPS Annual Social and Economic Supplement (ASEC). Similar to the March Supplement, the fertility supplement of the Current Population Survey asks women (either by self-response of proxy) questions about childbirth. Several fertility supplement samples also contain marital history information. This paper uses both the March Supplement and the June supplement. The following figures show that data from the two supplements are consistent with each other, and nothing essential would be missing if I use one of them.

Figure 1.8: CPS Data Comparison: March Sample, June Sample, Full Sample




(a) Unpartnered (b) Cohabiting (c) Married

Source: CPS March Supplement and FRED

**Marital Status and Fertility Evolution (Base Group: Unpartnered)**

Table 1.20: Tendency to have children

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | birth | birth | birth | birth |
| cohabiting | 0.0239 | 0.0486 | 0.0233 | 0.0248 |
| | (0.0421) | (0.0416) | (0.0421) | (0.0421) |
| married | 0.792*** | 0.774*** | 0.792*** | 0.792*** |
| | (0.0192) | (0.0190) | (0.0192) | (0.0192) |
| BA+ | -0.440*** | | -0.440*** | -0.536*** |
| | (0.0191) | | (0.0191) | (0.0481) |
| Years | No | Yes | Yes | Yes |
| Years×Edu | No | No | No | Yes |
| Constant | -3.818 | -5.635 | -3.682 | -3.807 |
| | (9.369) | (9.288) | (9.373) | (9.376) |
| Observations | 27964 | 27964 | 27964 | 27964 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.21: Completed Fertility

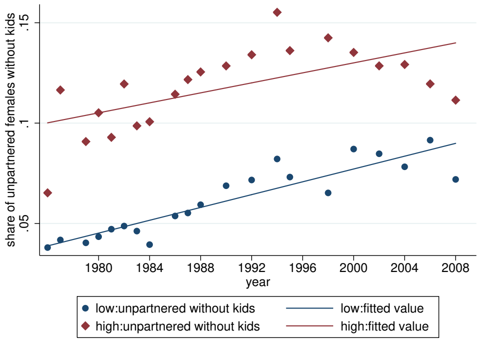
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | fertility | fertility | fertility | fertility |
| cohabiting | 0.0801 | 0.0891* | 0.0815* | 0.0826* |
| | (0.0413) | (0.0414) | (0.0413) | (0.0413) |
| married | 0.159*** | 0.146*** | 0.160*** | 0.161*** |
| | (0.0166) | (0.0166) | (0.0166) | (0.0166) |
| BA+ | -0.133*** | | -0.133*** | -0.133** |
| | (0.0155) | | (0.0155) | (0.0420) |
| Years | No | Yes | Yes | Yes |
| Years×Edu | No | No | No | Yes |
| Constant | -12.31 | -12.80 | -12.49 | -12.53 |
| | (7.196) | (7.208) | (7.196) | (7.197) |
| Observations | 22308 | 22308 | 22308 | 22308 |

Standard errors in parentheses

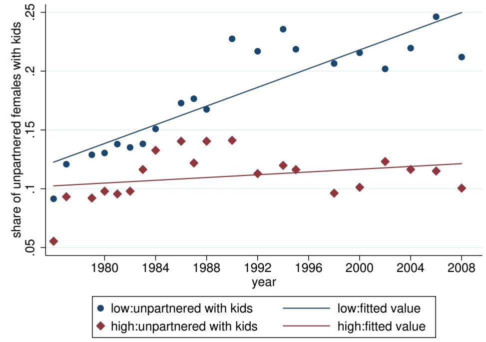
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## Detailed Evolution of Marital Status by Fertility Decision

Figure 1.9: Share of Unpartnered Females

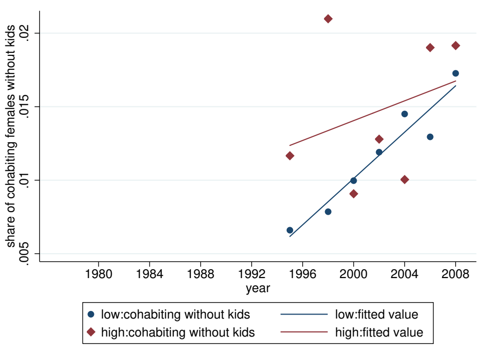



(a) without kids

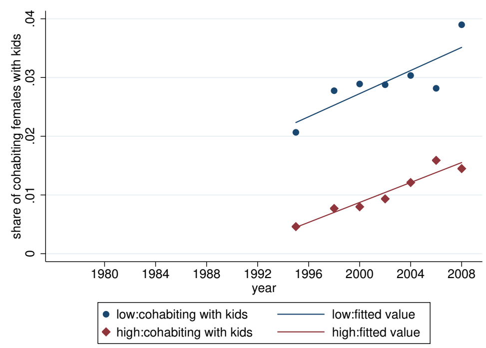



(b) with kids

Figure 1.10: Share of Cohabiting Females

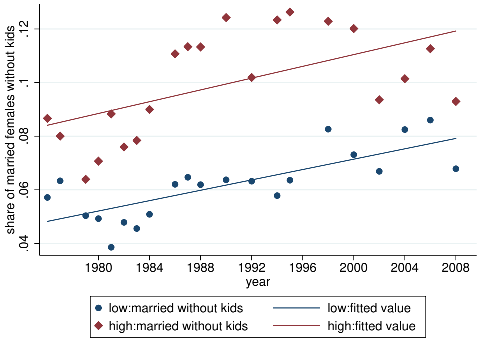



(a) without kids

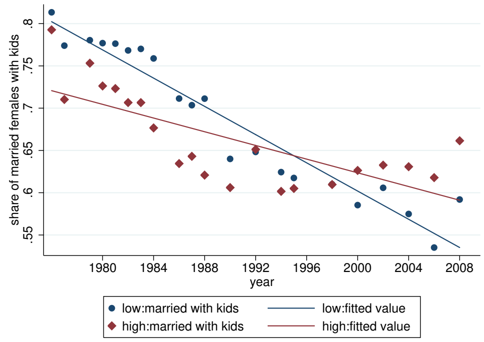



(b) with kids

Figure 1.11: Share of Married Females




(a) without kids




(b) with kids

## Detailed Distribution of Time Use

Figure 1.12: Distribution: Total Hours Usually Spent in Market Work

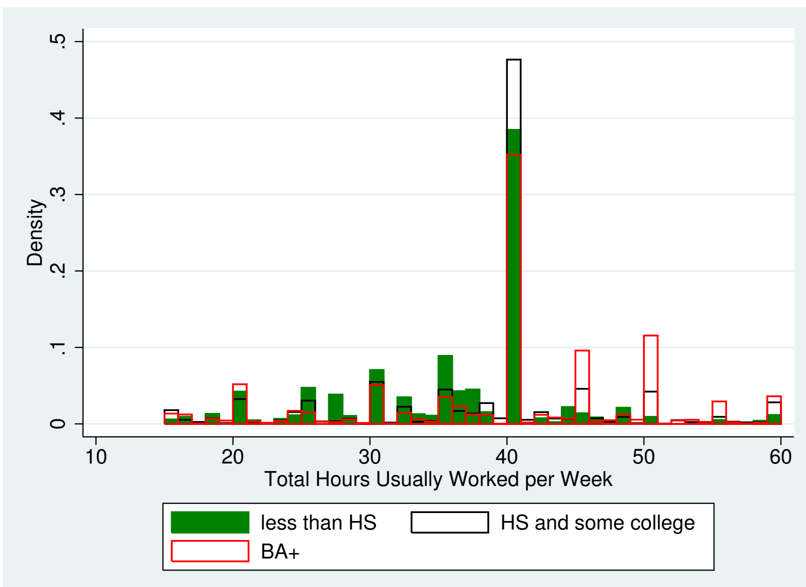
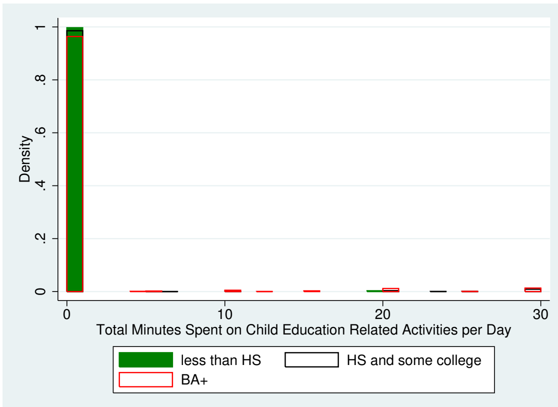
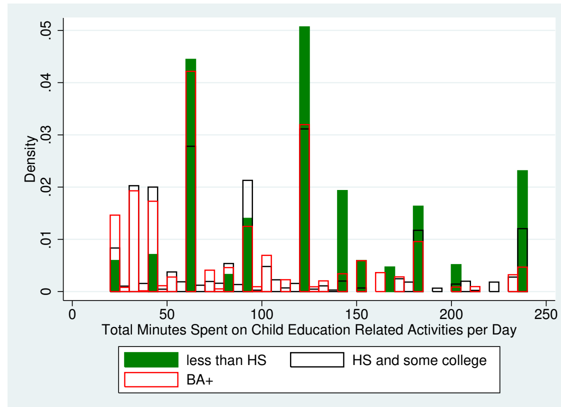


Figure 1.13: Distribution: Total Minutes Spent on Child Education Related Activities per Day

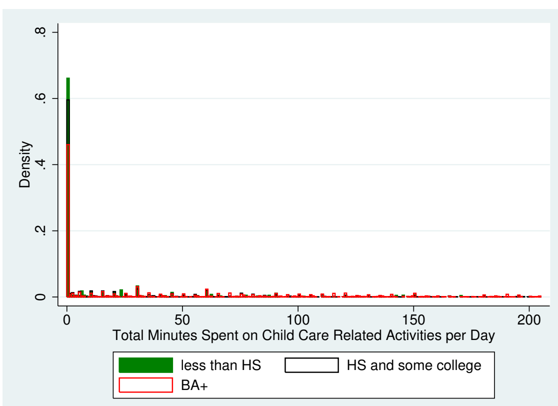



(a) full sample

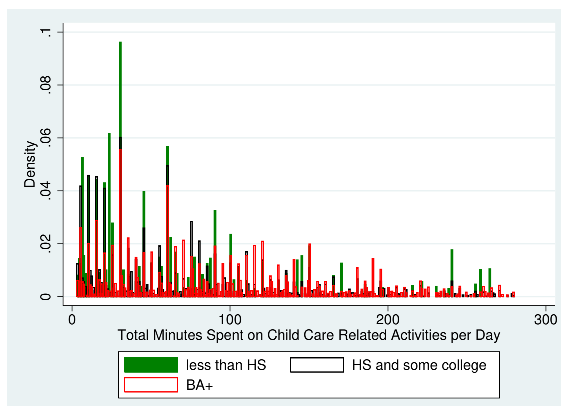



(b) excluding zero

Figure 1.14: Distribution: Total Minutes Spent on Child Education Related Activities per Day



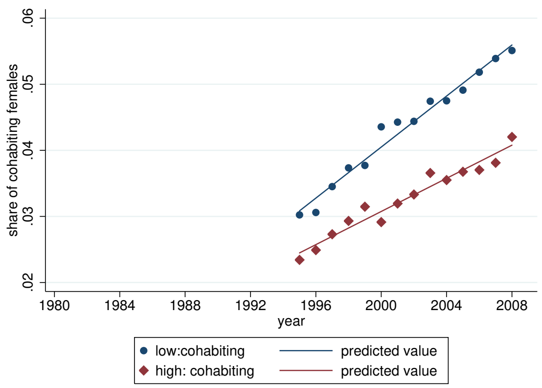

(a) full sample



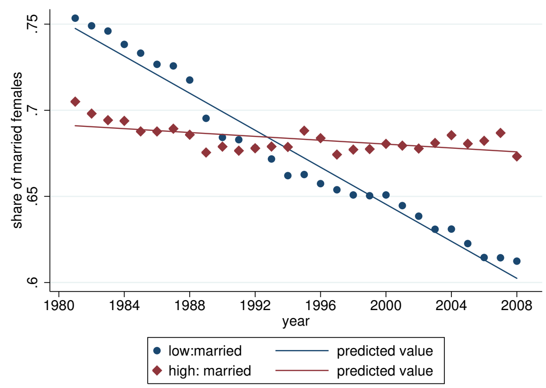

(b) excluding zero

## Robustness Check

Figure 1.15: Marriage Status for Females by Education Groups (20-65 years old)



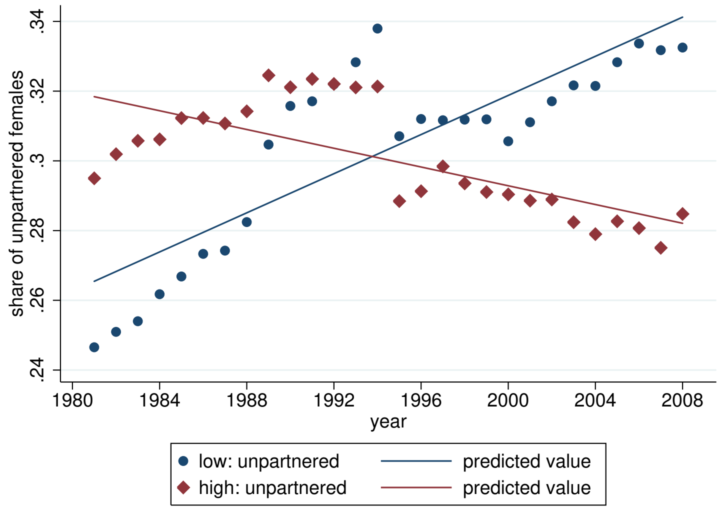

(a) cohabiting



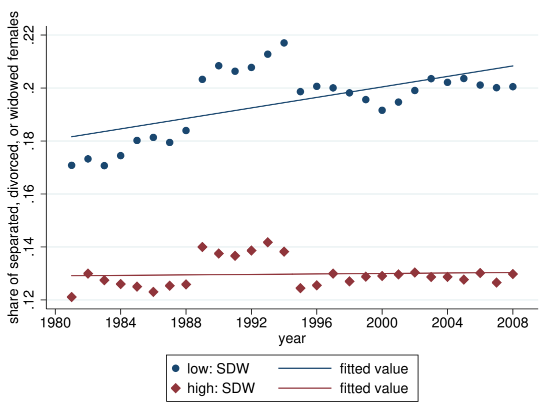

(b) married

Source: June CPS Supplement

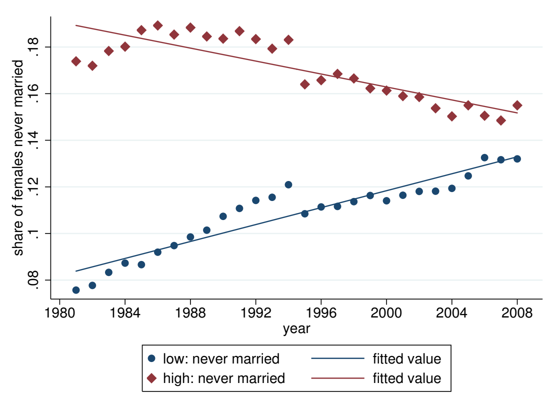
Figure 1.16: Marriage Status for Females by Education Groups cont. (20-65 years old)




(a) unpartnered



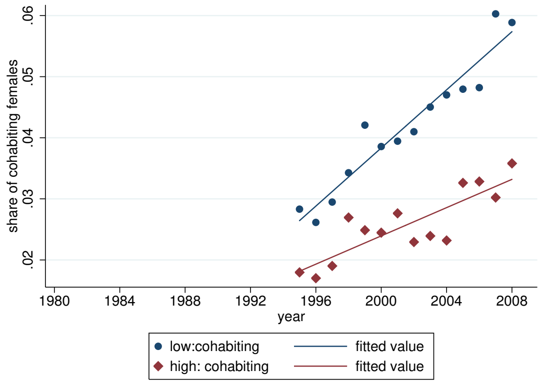

(b) separated, divorced, widowed



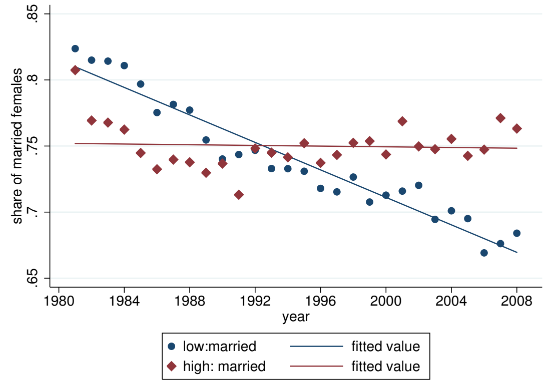

(c) never married (single)

Source: June CPS Supplement

Figure 1.17: Marriage Status for Females by Education Groups (40-45 years old, white)



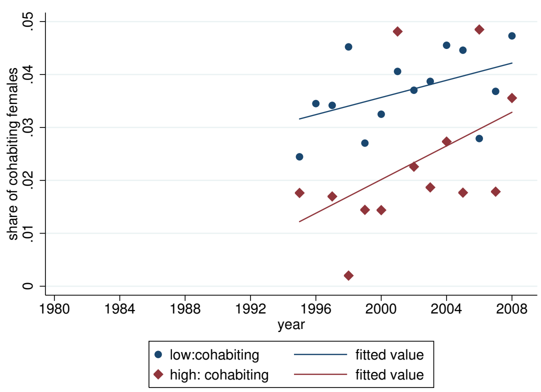

(a) cohabiting



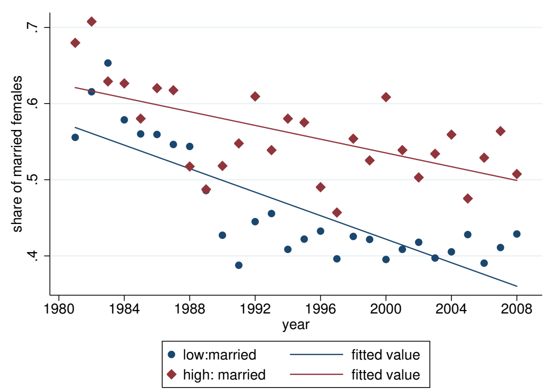

(b) married

Source: June CPS Supplement

Figure 1.18: Marriage Status for Females by Education Groups (40-45 years old, black)



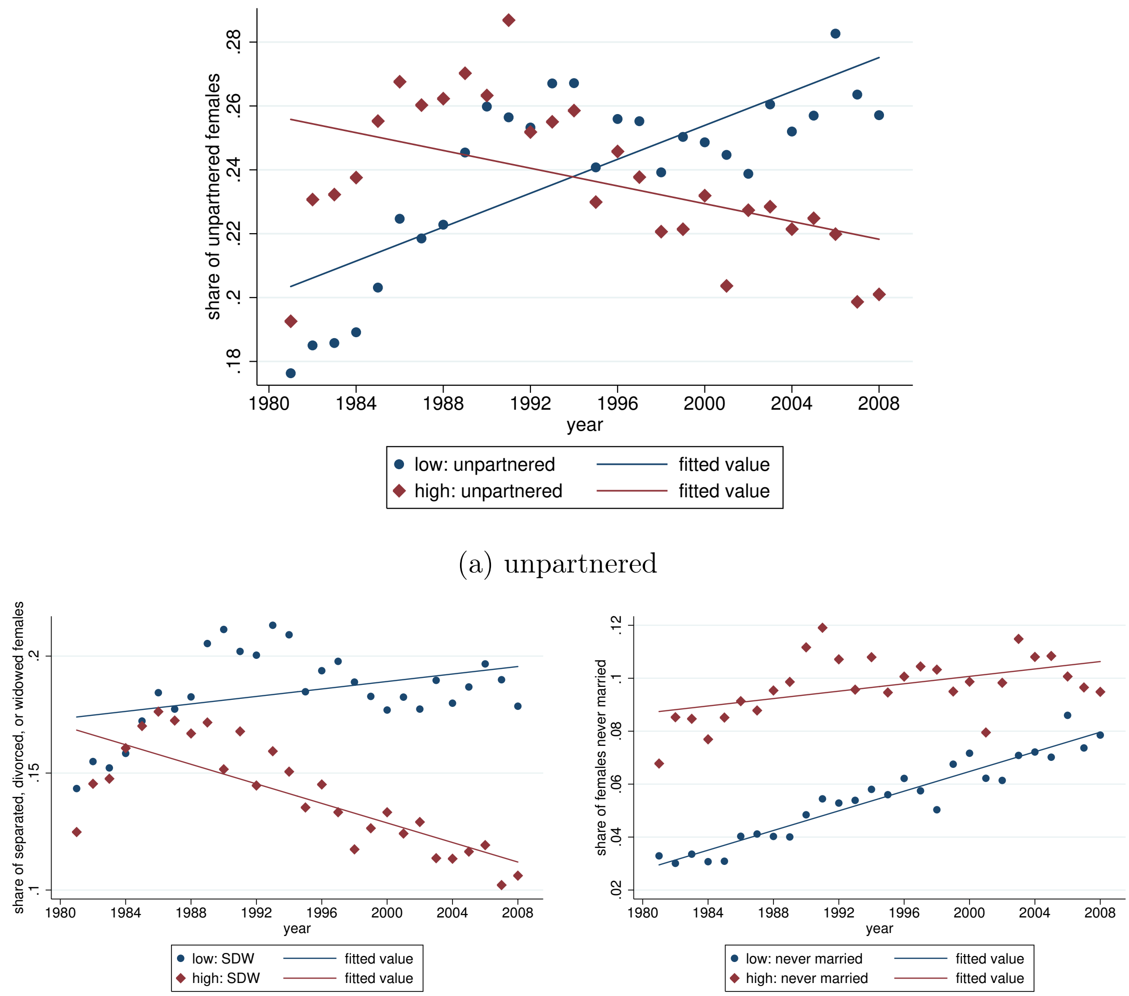

(a) cohabiting




(b) married

Source: June CPS Supplement

Figure 1.19: Marriage Status for Females by Education Groups cont. (40-45 years old, white)




(a) unpartnered

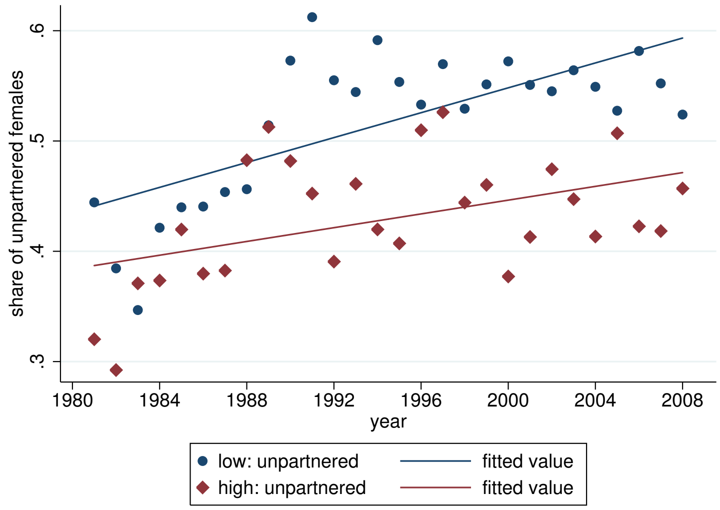


(b) separated, divorced, widowed

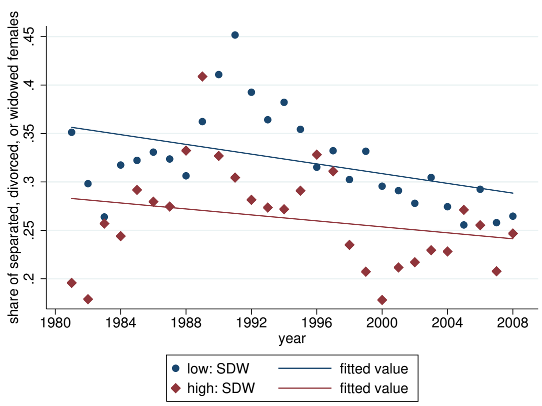
(c) never married (single)

Source: June CPS Supplement

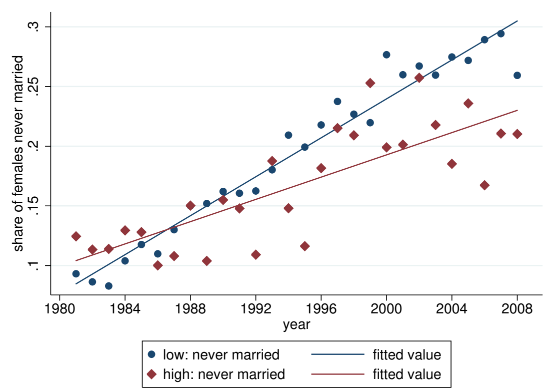
Figure 1.20: Marriage Status for Females by Education Groups cont. (40-45 years old, black)




(a) unpartnered



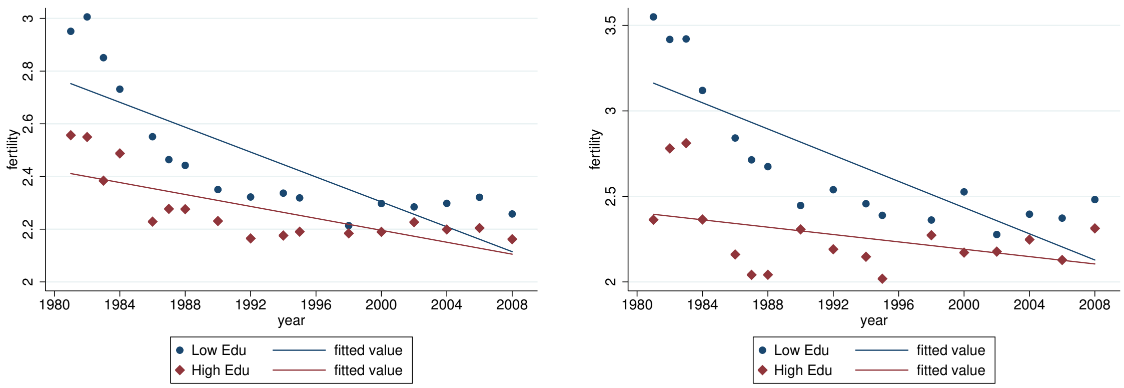

(b) separated, divorced, widowed




(c) never married (single)

Source: June CPS Supplement

Figure 1.21: Completed Fertility Rate by Ethnic Groups




(a) white females

(b) black females

Source: June CPS Supplement

### 1.9.3 Additional Tables

Table 1.22: Summary of Counterfactual Experiments

| | High-skilled | | | Low-skilled | | |
|---|---|---|---|---|---|---|
| | Cohabiting | Married | Fertility | Cohabiting | Married | Fertility |
| Exp1: $\omega^H$ | 0.5600 | -0.8000 | -0.1985 | — | — | — |
| Exp1: $\omega^L$ | — | — | — | -1.9200 | 2.2400 | 0.1626 |
| Exp2.1: $\pi_q^c$ | 0.8800 | -0.8400 | -0.0243 | 2.7200 | -2.8400 | -0.0805 |
| Exp2.1: $\pi_q^m$ | 0.8800 | -0.9600 | -2.1181 | 1.0800 | -1.2800 | 0.0124 |
| Exp2.2: $\pi_n^H$ | 1.1600 | -1.0000 | 0.1020 | — | — | — |
| Exp2.2: $\pi_n^L$ | 0.0000 | 0.0000 | 0.0000 | -0.8000 | 0.8000 | -0.1339 |
| Exp2.3: $\pi_0^H$ | 4.1600 | -4.2800 | 0.4007 | — | — | — |
| Exp2.3: $\pi_0^L$ | — | — | — | -3.8800 | 4.3200 | -0.4945 |
| Exp3.1: $\kappa^c$ | 0.0000 | 0.0000 | 0.0006 | 1.4400 | -1.6000 | -0.0571 |
| Exp3.1: $\kappa^m$ | -0.0400 | 0.0400 | -0.0038 | -0.0400 | 0.0400 | -0.0019 |
| Exp3.2: $B^H$ | -0.7600 | 0.8400 | 0.0071 | — | — | — |
| Exp3.2: $B^L$ | — | — | — | 0.3200 | -0.6800 | -0.0589 |
| Exp4: $s^c$ | -2.4000 | 2.1600 | 0.0166 | -4.4400 | 4.2800 | 0.0302 |
| Exp4: $s^m$ | -2.2800 | 4.0800 | 0.0679 | -4.0000 | 5.5200 | -0.0867 |
| Exp5.1: $\delta^c$ | 74.2800 | -72.5200 | 0.0931 | 66.5600 | -65.1200 | 0.1090 |
| Exp5.1: $\delta^m$ | 66.4000 | -69.3600 | 0.0713 | 59.9200 | -65.1200 | 0.0684 |
| Exp5.2: $\alpha_n^c$ | 0.2800 | -0.2800 | -0.0009 | -0.0800 | 0.0000 | 0.0098 |
| Exp5.2: $\alpha_n^m$ | 0.4800 | -0.4000 | 0.0007 | 2.1200 | -2.0000 | -0.0285 |

Table 1.23: Calibrated Parameters for Two Sub-Periods

| | Benchmark | First Period | Second Period |
|---|---|---|---|
| $B_H$ ($\uparrow$) | 1765 | 1760 | 1780 |
| $B_L$ ($\uparrow$) | 1505 | 1500 | 1525 |
| $\kappa^s$ ($\uparrow$) | 0.5500 | 0.4800 | 0.5900 |
| $\kappa^c$ ($\uparrow$) | 0.8600 | 0.7200 | 0.8700 |
| $\kappa^m$ ($\uparrow$) | 0.8800 | 0.7500 | 0.8900 |
| $\pi_q^s$ ($\uparrow$) | 0.0240 | 0.0237 | 0.0245 |
| $\pi_q^c$ ($\uparrow$) | 0.0220 | 0.0218 | 0.0225 |
| $\pi_q^m$ ($\uparrow$) | 0.0170 | 0.0168 | 0.0172 |
| $\pi_n^H$ ($\uparrow$) | 0.1967 | 0.1963 | 0.1970 |
| $\pi_n^L$ ($\uparrow$) | 0.1865 | 0.1864 | 0.1869 |
| $\delta^c$ ($\uparrow$) | 0.235 | 0.165 | 0.315 |
| $\pi_0^H$ ($\uparrow$) | 827.8038 (2.214%) | 506.2731 (1.390%) | 992.1032 (2.602%) |
| $\pi_0^L$ ($\uparrow$) | 493.0942 (2.789%) | 341.8998 (2.014%) | 597.6564 (3.251%) |
| $\overline{s_{man}^c}$ ($\uparrow$) | 0.5901 | 0.5680 | 0.6122 |
| $\overline{s_{man}^m}$ ($\uparrow$) | 0.4595 | 0.4555 | 0.4635 |

Table 1.24: Dynamics Calibration Targets

| | | Single | Cohabiting | Married | Fertility | HC Growth |
|---|---|---|---|---|---|---|
| Data | High | 12.6721 | 3.2389 | 84.0890 | 2.2083 | 1.0121 |
| | Low | 13.2161 | 5.6485 | 81.1354 | 2.3158 | 1.0260 |
| Model | High | 12.5200 | 3.8400 | 83.6400 | 2.2560 | 1.0667 |
| | Low | 9.0400 | 8.8400 | 82.1200 | 2.8123 | 1.0327 |

(a) second sub-period

| | | Single | Cohabiting | Married | Fertility | HC Growth |
|---|---|---|---|---|---|---|
| Data | High | 12.8043 | 2.3995 | 84.7962 | 2.2101 | 1.0121 |
| | Low | 10.6154 | 4.2887 | 85.0959 | 2.3301 | 1.0262 |
| Model | High | 13.2400 | 3.0800 | 83.6800 | 2.7935 | 0.9468 |
| | Low | 9.6800 | 5.8400 | 84.4800 | 3.0151 | 1.0110 |

(b) first sub-period

| | | Single | Cohabiting | Married | Fertility | HC Growth |
|---|---|---|---|---|---|---|
| Data | High | -0.1322 | 0.8394 | -0.7072 | -0.0018 | 0.0000 |
| | Low | 2.6008 | 1.3598 | -3.9605 | -0.0143 | -0.0002 |
| Model | High | -0.7200 | 0.7600 | -0.0400 | -0.5374 | 0.1200 |
| | Low | -0.6400 | 3.0000 | -2.3600 | -0.2028 | 0.0216 |

(c) difference between sub-periods

Table 1.25: Dynamics Model Predictions

| | | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|
| Data | High | 1.8094 | 1.9336 | 2.2248 |
| | Low | 2.1201 | 2.2699 | 2.3358 |
| Model | High | 1.6524 | 2.0206 | 2.3858 |
| | Low | 1.9887 | 2.4340 | 2.9978 |

(a) second sub-period

| | | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|
| Data | High | 1.9723 | 1.9553 | 2.2169 |
| | Low | 2.1201 | 2.2699 | 2.3358 |
| Model | High | 2.2888 | 2.1507 | 2.9480 |
| | Low | 2.4515 | 2.9586 | 3.1161 |

(b) first sub-period

| | | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|
| Data | High | -0.1629 | -0.0217 | 0.0079 |
| | Low | -0.0145 | -0.0138 | -0.0081 |
| Model | High | -0.6364 | -0.1301 | -0.5622 |
| | Low | -0.4628 | -0.5247 | -0.1183 |

(c) difference between sub-periods

Table 1.26: Dynamics Counterfactual Experiment 1: Wage and Skill Premium

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3970 | 7.0953 | 82.5077 | 2.6164 | 1.8552 | 2.1651 | 2.7963 | 1.0459 |
| High | 12.6800 | 4.1600 | 83.1600 | 2.2869 | 1.6306 | 1.7129 | 2.4572 | 1.0683 |
| Low | 9.0400 | 8.8400 | 82.1200 | 2.8123 | 1.9887 | 2.4340 | 2.9978 | 1.0327 |
| Diff | 3.6400 | -4.6800 | 1.0400 | -0.5254 | -0.3582 | -0.7211 | -0.5406 | 0.0356 |
| Diff wrt model (High) | 0.1600 | 0.3200 | -0.4800 | 0.0308 | -0.0218 | -0.3078 | 0.0713 | 0.0016 |
| Diff wrt model (Low) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

(a) $\omega_H \downarrow$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.4126 | 3.6393 | 85.9481 | 2.5565 | 1.8296 | 1.3817 | 2.7498 | 1.0911 |
| High | 12.5200 | 3.8400 | 83.6400 | 2.2560 | 1.6524 | 2.0206 | 2.3858 | 1.0667 |
| Low | 9.1600 | 3.5200 | 87.3200 | 2.7350 | 1.9350 | 1.0020 | 2.9662 | 1.1056 |
| Diff | 3.3600 | 0.3200 | -3.6800 | -0.4790 | -0.2826 | 1.0186 | -0.5803 | -0.0389 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Diff wrt model (Low) | 0.1200 | -5.3200 | 5.2000 | -0.0773 | -0.0538 | -1.4320 | -0.0316 | 0.0729 |

(b) $\omega_L \downarrow$

Table 1.27: Dynamics Counterfactual Experiment 2.1: Effort Cost of Childrearing

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.4220 | 6.7211 | 82.8568 | 2.6092 | 1.8664 | 2.3210 | 2.7697 | 1.0468 |
| High | 12.6800 | 3.5600 | 83.7600 | 2.2582 | 1.6571 | 2.0638 | 2.3858 | 1.0671 |
| Low | 9.0800 | 8.6000 | 82.3200 | 2.8178 | 1.9907 | 2.4738 | 2.9978 | 1.0348 |
| Diff | 3.6000 | -5.0400 | 1.4400 | -0.5596 | -0.3337 | -0.4100 | -0.6120 | 0.0323 |
| Diff wrt model (High) | 0.1600 | -0.2800 | 0.1200 | 0.0022 | 0.0047 | 0.0432 | 0.0000 | 0.0004 |
| Diff wrt model (Low) | 0.0400 | -0.2400 | 0.2000 | 0.0055 | 0.0020 | 0.0398 | 0.0000 | 0.0021 |

(a) $\pi_q^c \downarrow$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.4370 | 7.4927 | 82.0703 | 2.6103 | 1.8665 | 2.2511 | 2.7874 | 1.0436 |
| High | 12.7200 | 3.8800 | 83.4000 | 2.3282 | 1.6563 | 2.0905 | 2.4780 | 1.0423 |
| Low | 9.0800 | 9.6400 | 81.2800 | 2.7780 | 1.9914 | 2.3466 | 2.9713 | 1.0444 |
| Diff | 3.6400 | -5.7600 | 2.1200 | -0.4498 | -0.3351 | -0.2561 | -0.4933 | -0.0021 |
| Diff wrt model (High) | 0.2000 | 0.0400 | -0.2400 | 0.0721 | 0.0039 | 0.0699 | 0.0922 | -0.0245 |
| Diff wrt model (Low) | 0.0400 | 0.8000 | -0.8400 | -0.0343 | 0.0026 | -0.0874 | -0.0265 | 0.0117 |

(b) $\pi_q^m \downarrow$

Table 1.28: Dynamics Counterfactual Experiment 2.2: Time Cost of Childrearing

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3373 | 6.9760 | 82.6866 | 2.6077 | 1.8654 | 2.2819 | 2.7726 | 1.0451 |
| High | 12.5200 | 3.8400 | 83.6400 | 2.2635 | 1.6580 | 2.0260 | 2.3937 | 1.0660 |
| Low | 9.0400 | 8.8400 | 82.1200 | 2.8123 | 1.9887 | 2.4340 | 2.9978 | 1.0327 |
| Diff | 3.4800 | -5.0000 | 1.5200 | -0.5488 | -0.3308 | -0.4080 | -0.6041 | 0.0334 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0074 | 0.0056 | 0.0054 | 0.0079 | -0.0007 |
| Diff wrt model (Low) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

(a) $\pi_n^H \downarrow$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3122 | 5.6213 | 84.0665 | 2.5688 | 1.8649 | 2.5946 | 2.6760 | 1.0690 |
| High | 12.5200 | 3.8400 | 83.6400 | 2.2560 | 1.6524 | 2.0206 | 2.3858 | 1.0667 |
| Low | 9.0000 | 6.6800 | 84.3200 | 2.7548 | 1.9912 | 2.9358 | 2.8485 | 1.0703 |
| Diff | 3.5200 | -2.8400 | -0.6800 | -0.4987 | -0.3389 | -0.9151 | -0.4627 | -0.0036 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Diff wrt model (Low) | -0.0400 | -2.1600 | 2.2000 | -0.0575 | 0.0025 | 0.5018 | -0.1493 | 0.0376 |

(b) $\pi_n^L \downarrow$

Table 1.29: Dynamics Counterfactual Experiment 2.3: Resource Cost of Childrearing

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.5908 | 7.5874 | 81.8218 | 2.8225 | 2.1175 | 2.2922 | 3.0128 | 0.9962 |
| High | 13.2000 | 5.4800 | 81.3200 | 2.8396 | 2.3341 | 2.0538 | 3.0381 | 0.9350 |
| Low | 9.0400 | 8.8400 | 82.1200 | 2.8123 | 1.9887 | 2.4340 | 2.9978 | 1.0327 |
| Diff | 4.1600 | -3.3600 | -0.8000 | 0.0273 | 0.3454 | -0.3802 | 0.0403 | -0.0977 |
| Diff wrt model (High) | 0.6800 | 1.6400 | -2.3200 | 0.5835 | 0.6818 | 0.0332 | 0.6523 | -0.1318 |
| Diff wrt model (Low) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

(a) $\pi_0^H \downarrow$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.6384 | 6.4492 | 82.9124 | 2.8314 | 2.2023 | 2.7246 | 2.9515 | 1.0139 |
| High | 12.5200 | 3.8400 | 83.6400 | 2.2560 | 1.6524 | 2.0206 | 2.3858 | 1.0667 |
| Low | 9.5200 | 8.0000 | 82.4800 | 3.1733 | 2.5291 | 3.1430 | 3.2877 | 0.9825 |
| Diff | 3.0000 | -4.1600 | 1.1600 | -0.9173 | -0.8767 | -1.1224 | -0.9019 | 0.0843 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Diff wrt model (Low) | 0.4800 | -0.8400 | 0.3600 | 0.3610 | 0.5404 | 0.7090 | 0.2899 | -0.0502 |

(b) $\pi_0^L \downarrow$

Table 1.30: Dynamics Counterfactual Experiment 3.1: Return of Investment in Children

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3820 | 6.4229 | 83.1950 | 2.5984 | 1.8647 | 2.1123 | 2.7697 | 1.0501 |
| High | 12.6400 | 2.7600 | 84.6000 | 2.2475 | 1.6560 | 1.6693 | 2.3858 | 1.0746 |
| Low | 9.0400 | 8.6000 | 82.3600 | 2.8069 | 1.9887 | 2.3756 | 2.9978 | 1.0355 |
| Diff | 3.6000 | -5.8400 | 2.2400 | -0.5594 | -0.3327 | -0.7063 | -0.6120 | 0.0391 |
| Diff wrt model (High) | 0.1200 | -1.0800 | 0.9600 | -0.0086 | 0.0036 | -0.3513 | 0.0000 | 0.0079 |
| Diff wrt model (Low) | 0.0000 | -0.2400 | 0.2400 | -0.0054 | 0.0000 | -0.0584 | 0.0000 | 0.0028 |

(a) $\kappa^c \downarrow$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3624 | 7.2840 | 82.3536 | 2.5587 | 1.8650 | 2.1563 | 2.7231 | 1.0381 |
| High | 12.5200 | 3.3200 | 84.1600 | 2.2290 | 1.6524 | 1.8276 | 2.3592 | 1.0627 |
| Low | 9.0800 | 9.6400 | 81.2800 | 2.7546 | 1.9914 | 2.3517 | 2.9394 | 1.0235 |
| Diff | 3.4400 | -6.3200 | 2.8800 | -0.5256 | -0.3390 | -0.5242 | -0.5802 | 0.0392 |
| Diff wrt model (High) | 0.0000 | -0.5200 | 0.5200 | -0.0271 | 0.0000 | -0.1931 | -0.0266 | -0.0041 |
| Diff wrt model (Low) | 0.0400 | 0.8000 | -0.8400 | -0.0577 | 0.0026 | -0.0822 | -0.0584 | -0.0092 |

(b) $\kappa^m \downarrow$

Table 1.31: Dynamics Counterfactual Experiment 3.2: Return of Investment in Children

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3373 | 6.8120 | 82.8507 | 2.6021 | 1.8622 | 2.2132 | 2.7691 | 1.0423 |
| High | 12.5200 | 3.4000 | 84.0800 | 2.2486 | 1.6492 | 1.8418 | 2.3844 | 1.0585 |
| Low | 9.0400 | 8.8400 | 82.1200 | 2.8123 | 1.9887 | 2.4340 | 2.9978 | 1.0327 |
| Diff | 3.4800 | -5.4400 | 1.9600 | -0.5637 | -0.3395 | -0.5921 | -0.6134 | 0.0258 |
| Diff wrt model (High) | 0.0000 | -0.4400 | 0.4400 | -0.0075 | -0.0031 | -0.1788 | -0.0014 | -0.0083 |
| Diff wrt model (Low) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

(a) $B^H \downarrow$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3373 | 3.6644 | 85.9983 | 2.5711 | 1.8610 | 1.4647 | 2.7561 | 1.0715 |
| High | 12.5200 | 3.8400 | 83.6400 | 2.2560 | 1.6524 | 2.0206 | 2.3858 | 1.0667 |
| Low | 9.0400 | 3.5600 | 87.4000 | 2.7583 | 1.9851 | 1.1342 | 2.9762 | 1.0744 |
| Diff | 3.4800 | 0.2800 | -3.7600 | -0.5023 | -0.3327 | 0.8864 | -0.5904 | -0.0077 |
| Diff wrt model (High) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Diff wrt model (Low) | 0.0000 | -5.2800 | 5.2800 | -0.0540 | -0.0036 | -1.2997 | -0.0216 | 0.0417 |

(b) $B^L \downarrow$

Table 1.32: Dynamics Counterfactual Experiment 4: Commitment of Partner

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.3820 | 7.5630 | 82.0550 | 2.5525 | 1.8600 | 1.7071 | 2.7697 | 1.0548 |
| High | 12.6400 | 1.0400 | 86.3200 | 2.2540 | 1.6542 | 1.2806 | 2.3858 | 1.0852 |
| Low | 9.0400 | 11.4400 | 79.5200 | 2.7299 | 1.9824 | 1.9606 | 2.9978 | 1.0368 |
| Diff | 3.6000 | -10.4000 | 6.8000 | -0.4759 | -0.3281 | -0.6799 | -0.6120 | 0.0484 |
| Diff wrt model (High) | 0.1200 | -2.8000 | 2.6800 | -0.0020 | 0.0019 | -0.7400 | 0.0000 | 0.0185 |
| Diff wrt model (Low) | 0.0000 | 2.6000 | -2.6000 | -0.0824 | -0.0063 | -0.4734 | 0.0000 | 0.0041 |

(a) $s^c \downarrow$

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.5115 | 6.9990 | 82.4895 | 2.6033 | 1.8663 | 2.4101 | 2.7488 | 1.0439 |
| High | 12.9200 | 4.4400 | 82.6400 | 2.3286 | 1.6607 | 1.9957 | 2.4891 | 1.0230 |
| Low | 9.0800 | 8.5200 | 82.4000 | 2.7667 | 1.9885 | 2.6564 | 2.9031 | 1.0563 |
| Diff | 3.8400 | -4.0800 | 0.2400 | -0.4381 | -0.3277 | -0.6607 | -0.4140 | -0.0333 |
| Diff wrt model (High) | 0.4000 | 0.6000 | -1.0000 | 0.0725 | 0.0084 | -0.0250 | 0.1033 | -0.0437 |
| Diff wrt model (Low) | 0.0400 | -0.3200 | 0.2800 | -0.0456 | -0.0002 | 0.2224 | -0.0947 | 0.0237 |

(b) $s^m \downarrow$

Table 1.33: Dynamics Counterfactual Experiment 5: Direct Cohabitation Preference

| Edu Group | Single | Cohabiting | Married | Fertility | HC Growth | S Fertility | C Fertility | M Fertility |
|---|---|---|---|---|---|---|---|---|
| Total | 10.5312 | 4.1796 | 85.2893 | 2.5876 | 1.8626 | 1.5510 | 2.7697 | 1.0687 |
| High | 13.0400 | 0.0400 | 86.9200 | 2.2639 | 1.6610 | 0.8618 | 2.3858 | 1.0856 |
| Low | 9.0400 | 6.6400 | 84.3200 | 2.7800 | 1.9824 | 1.9606 | 2.9978 | 1.0586 |
| Diff | 4.0000 | -6.6000 | 2.6000 | -0.5161 | -0.3214 | -1.0988 | -0.6120 | 0.0269 |
| Diff wrt model (High) | 0.5200 | -3.8000 | 3.2800 | 0.0078 | 0.0087 | -1.1588 | 0.0000 | 0.0189 |
| Diff wrt model (Low) | 0.0000 | -2.2000 | 2.2000 | -0.0323 | -0.0063 | -0.4734 | 0.0000 | 0.0260 |

(a) $\delta^c \downarrow$

# Chapter 2

# Skill Biased Entrepreneurial Decline

Helu Jiang[1] Faisal Sohail[2]

## 2.1 Introduction

The secular decline in business dynamism in the United States has motivated an extensive and growing literature that attempts to understand the cause and consequences of this phenomenon[3]. This decline is evident in the pace of job creation, destruction, and other measures of firm volatility and growth. An important component of these changes, and one that has attracted particular attention, is the slowdown of new firm startups e.g. Decker et al. (2014) and Karahan et al. (2018). As younger businesses tend to grow faster and have outsized contributions to gross job creation, understanding the forces driving their relative decline in entry is important for predicting future changes in business dynamism and the impact of potential policies.

Our contribution to this understanding is two-fold. First, we provide evidence showing

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[3]See Davis et al. (1998); Decker et al. (2013); Pugsley and Sahin (2015)and references therein.

a differential change in the overall, entry and exit rates of self-employment across skilled and unskilled individuals.[4] Skill level is an important dimension to explore as more skilled entrepreneurs tend to operate more successful enterprises and hence contribute more to the aggregate economy e.g. Doms et al. (2010) and Levine and Rubinstein (2016). Furthermore, the presence of any skill bias in the decline in entrepreneurial entry and activity will have different aggregate implications and call for different policy responses. We show that this is indeed the case and that the overall decline in entry is more pronounced amongst skilled individuals.

Using matched data from the Current Population Survey (CPS) we show that transitions from employment to self-employment fell much more for those with at least a college degree compared to those with a high school degree or some college experience between 1983 and 2017. We find similar results when considering the share of self-employed in total employment and the rate of exit from entrepreneurship across skill groups. Intuitively, if individuals make an occupational choice between employment and self-employment by comparing earnings in either occupation then these findings reflect differences in the evolution of earnings in employment and entrepreneurship across skill groups. Indeed, this suggests that worker's earnings have risen faster than entrepreneurial earnings for skilled individuals and relatively slower for unskilled individuals. This intuition is empirically tested by studying the evolution of the skill premium for workers and entrepreneurs. Indeed, we show that the latter grew much faster than the former. When comparing the evolution of the earnings distribution across occupations and within skill groups we find that worker's earnings grew faster than entrepreneurial earnings for skilled individuals, while the two have grown at a similar pace for unskilled individuals. Hence understanding the skill biased decline in entrepreneurship

[4] Along the lines of Levine and Rubinstein (2016), we think of self-employment as being a necessary, but not sufficient, condition for entrepreneurship, that is, new product innovation, the formation of a firm with employees etc. Hence, the study of self-employment can be applied to entrepreneurship. As such, throughout this paper we will refer to self-employment and entrepreneurship interchangeably.

should incorporate the changes in earnings structure of employees and the self-employed.

Our second contribution is, motivated by the evidence described above, to answer the following question: how much of the decline in entry in entrepreneurship can be attributed to the rise in worker's skill premium? To address this question we extend the occupational choice framework of Lucas (1978) and introduce heterogeneity in ability in both self-employment and wage work. Entrepreneurs have access to a CES production function and hire skilled and unskilled labor to produce. The rise in worker skill premium is assumed to be driven by skill biased technological change in the production function. While this framework does not allow us to study features such as exit and dynamics it does allow us to exactly identify the share of entrepreneurs in the population which we take to be the entry rate into entrepreneurship. In the data we find that between 1983 and 2006 the entry rate into entrepreneurship for skilled and unskilled individuals change by -11% and 18% respectively. The model generated figures for these values are -7% and 12% respectively. In other words, around two-thirds of the skill biased and subsequently aggregate decline in self-employment can be attributed to the rising worker skill premium or skill biased technical change. However, the model is unable to match the observed entrepreneurial skill premium.

Ultimately, we interpret the results from this simple model as suggesting an important role for the rising worker skill premium in explaining the differential decline in entry across skill groups. This in turn, contributes to our understanding of the broader decline in dynamism in the US and elsewhere[5].

**Related Literature** This paper contributes primarily to two strands of literature. The first is the literature that studies the evolution of the earnings structure of workers and entrepreneurs. The rising skill premium from wage work has been extensively studied since Katz and Murphy (1992) and Acemoglu and Autor (2011) provides a review. We borrow from this literature by introducing skill biased technological change, which determines

[5]See Calvino et al. (2016) for evidence on the decline in firm startups in OECD countries.

the worker skill premium, into a model of occupational choice and study the resulting impact on entrepreneurship. We contribute to this literature by measuring the skill premium for entrepreneurs and comparing it to that of workers. Unlike wage work, the returns to self-employment are difficult to define and is perhaps a reason why the skill premium to entrepreneurship is relatively unexplored. A notable exception is Michelacci and Schivardi (2016) who use data from the Survey of Consumer Finances (SCF) to construct a measure of life-time expected entrepreneurial returns. They compare the a naive measures of the skill premium for both workers and entrepreneurs and show that these have grown at a similar pace - other than the premium for the very highly educated. In contrast, we use the flow of entrepreneurial income and, after controlling for observables, find that the return to education for workers has increased faster than that for entrepreneurs.[6] While accounting for the continuation value in entrepreneurship is indeed important, the self-reported capital gains and sample selection bias on failed firms in the SCF may lead to estimates of entrepreneurial return that may not be clearly generalized. Furthermore,Michelacci and Schivardi (2016) also include older individuals above the age of 65 in their sample while we do not. This is an important distinction since older individuals are less likely to transition between employment and entrepreneurship - a key focus of our study.

The second strand of literature that we relate to, attempts to understand and document the decline in firm entry and dynamism in the US. Decker et al. (2013),Decker et al. (2014),Hathaway and Litan (2014) and Pugsley and Sahin (2015) use firm level data to document a falling entry rate for new firms across industries and geography since the late 1970s. Unlike these and related works, we use individual level data to highlight a similar phenomenon in the both the stock and flows of the self-employed.[7] Individual level data

[6]The CPS measures of yearly returns to entrepreneurship matches closely the income flows reported in the SCF.

[7]Fairlie et al. (2015) also use the CPS to document trends in entrepreneurial entry and exit across several demographic characteristics. In contrast to them, we focus only on individuals that enter into full-time entrepreneurship from full-time wage-work (or vice-versa). We also extend their sample period used by

allows us to disaggregate, among other dimensions, by the skill level of the founders of an enterprise and provide insight into the underlying cause driving the declines in firm entry.[8] More recently, Karahan et al. (2018) and Hopenhayn et al. (2018), study the relationship between the slowing growth rate of the labor force and the declines in new firm formation. These works abstract from the skill level of entrepreneurs and focus instead on the aggregate trends.

This paper is most closely related to Salgado (2018) who uses the Panel Study of Income Dynamics (PSID) to document a skill biased decline in overall and entry into self-employment. Salgado (2018) then studies the role of a rising skill premium and lower capital costs in driving this decline through the lens of an occupational choice model. Our work is distinct in several important dimensions. First, our use of the CPS allows for a more complete coverage of the population of potential and existing entrepreneurs. In particular, the author's sample of household heads in the PSID under-states the share of i) female and ii) non-white entrepreneurs. This is an important restriction since, as we document in the appendix, the evolution of the overall share and entry into self-employment for the sample excluded in Salgado (2018) has been more muted. Indeed, using the more complete CPS data, we find a significant *increase* in transitions into entrepreneurship for unskilled individuals - a finding that we match in our quantitative analysis. A second point of departure between our work and Salgado (2018) is that we document the evolution of the exit rate from self-employment into wage work by skill group. As we argue below, understanding flows both in and out of self-employment are critical for understanding the overall decline in the share of entrepreneurs. Finally, we perform a number of robustness checks that provide empirical support for a causal impact of a rising worker skill premium and skill biased entrepreneurial decline. This includes comparing the entrepreneurial and worker skill premium, and studying

including data from years prior to the 1994 CPS redesign.

[8] We include in appendix 2.8 a discussion on the comparability of individual level data in the CPS and firm level data in the Business Dynamics Statistics (BDS).

this self-employment across states.

An outline of the paper follows. Section 2.2 details the primary empirical evidence while section 2.3 includes a number of robustness checks discussion on entrepreneurial polarization. Section 2.4 outlines the model and section 2.5 our calibration strategy. Section 2.6 presents our results and section 2.7 concludes.

## 2.2 Empirical Evidence

This section establishes the empirical facts that motivate this paper and discipline our model's calibration. First, we study, by skill type, the evolution of the i) overall share, ii) entry and iii) exit rates of self-employment and show that the aggregate decline in entrepreneurship has been pronounced among skilled individuals, and is driven primarily by differential entry rates by skill. Second, evidence on the evolution of earnings of entrepreneurs and workers across and within skill groups is presented. More specifically, we show that i) worker skill premium rose faster than that for entrepreneurs and ii) worker's earnings rose faster (at the same speed) than entrepreneurial earnings for skilled (unskilled) individuals. We then exploit differences in the growth of workers skill premium across states in the U.S. as evidence to support of our hypothesis that changes in workers wage structure to explain the skill biased decline in entrepreneurship. In particular, we show that those states which experienced larger increases in worker skill premium also display higher degree of skill bias in entrepreneurial decline. Before presenting this evidence in detail the data is described briefly.

**Data Description** The analysis of entry and exit into entrepreneurship is based primarily on the Integrated Public Use Microdata Series (IPUMS) CPS basic monthly files from 1983 to 2018.[9] Only those respondents that had obtained at least a high school degree are

[9]We start out analysis in 1983 as that is the first year that identifies both the incorporated and unincorporated self-employed in the CPS.

included in the sample. Furthermore, we include only those that were either employed by others or self-employed (both incorporated and unincorporated) in full-time, non-agricultural occupations between the ages of 25 and 65. We consider those individuals that have received at least a bachelor's degree or greater than 16 years of schooling to be skilled and the those with at least a high school but no college degree to be unskilled. To measure entry and exit rates we exploit the rotating panel nature of the monthly CPS and match an individual's occupation on an annual basis. By following respondents over time we can analyze transitions from employment to entrepreneurship and construct a measure of startup intensity for a given calendar month. Yearly estimates are obtained by pooling the monthly data. As a robustness exercise we redo this analysis using March CPS data and the Survey of Income and Program Participation (SIPP) as well as imposing additional data restrictions which are described in section 2.3. All data on earnings are obtained from the IPUMS March CPS. Details on the construction of all samples including the adjustment method used to accommodate the CPS redesigns and variables used to measure income are described in appendix 2.8.

### 2.2.1 Skill Biased Entrepreneurial Decline

Figure 2.1a shows that amongst all those employed either by themselves or others, the share of those self-employed has steadily declined for both skilled and unskilled individuals. Although constructed using individual-level data, this overall decline in entrepreneurship is consistent with findings using data on employer firms as in the BDS[10]. However, the richer data on individual entrepreneurs allows us to identify that this decline has been much more dramatic for skilled individuals. In 1985 around 10 percent of unskilled employment consisted of self-employment while the analogous measure for skilled individuals was around

[10] See e.g. Hathaway and Litan (2014) for similar evidence using BDS data. Hipple (2004) finds a similar trend for the aggregate self-employment rate and a limited set of years using the CPS monthly data.

13 percent. By the end of 2014 both groups had a similar share of self-employed of around 9 percent representing a 31 and 10 percent decline in the skilled and unskilled self-employment rate, respectively over the period. While the overall trend is clearly negative the figure also shows periods during which the self-employment rate was increasing. The most striking and prolonged deviation from trend took place between 2002 and 2005 when the the share of self-employed in total employment, for both groups, rose sharply by around one percentage point[11].

Notice that figure 2.1a captures changes in both the entry and exit margins of entrepreneurship. We disentangle these margins by using the matched CPS sample. Consider first the the entry rate into self-employment as shown in figure 2.1b. The figure plots the expected annual transition probability of a wage-worker entering self-employment from 1983 to 2014. It illustrates the differential changes in *entry into* self-employment amongst skilled and unskilled workers over this period. For instance, around 3.1 percent of skilled and 2.1 percent of unskilled employees entered entrepreneurship between 1983 and 1984. By 2006, this figure had declined to around 2.5 percent for skilled workers and increased to 2.2 percent for unskilled workers. This corresponds to a 11% decline and 18% increase in the entry rate for the skilled and unskilled respectively. As with the self-employment rate, the entry rate exhibits a relative skill bias in it's decline. Indeed, the two measures for skilled individuals track each other quite closely. For unskilled employees the entry rate does not decline and instead remains fairly flat, experiencing a few periods of increase in the mid to late 90's and early 2000's. The Great Recession impacted the entry rate for both populations in similar manner but while the transition probabilities for the unskilled had recovered by 2014 the analogous rate for skilled employees did not and remains low at 2.3 percent.

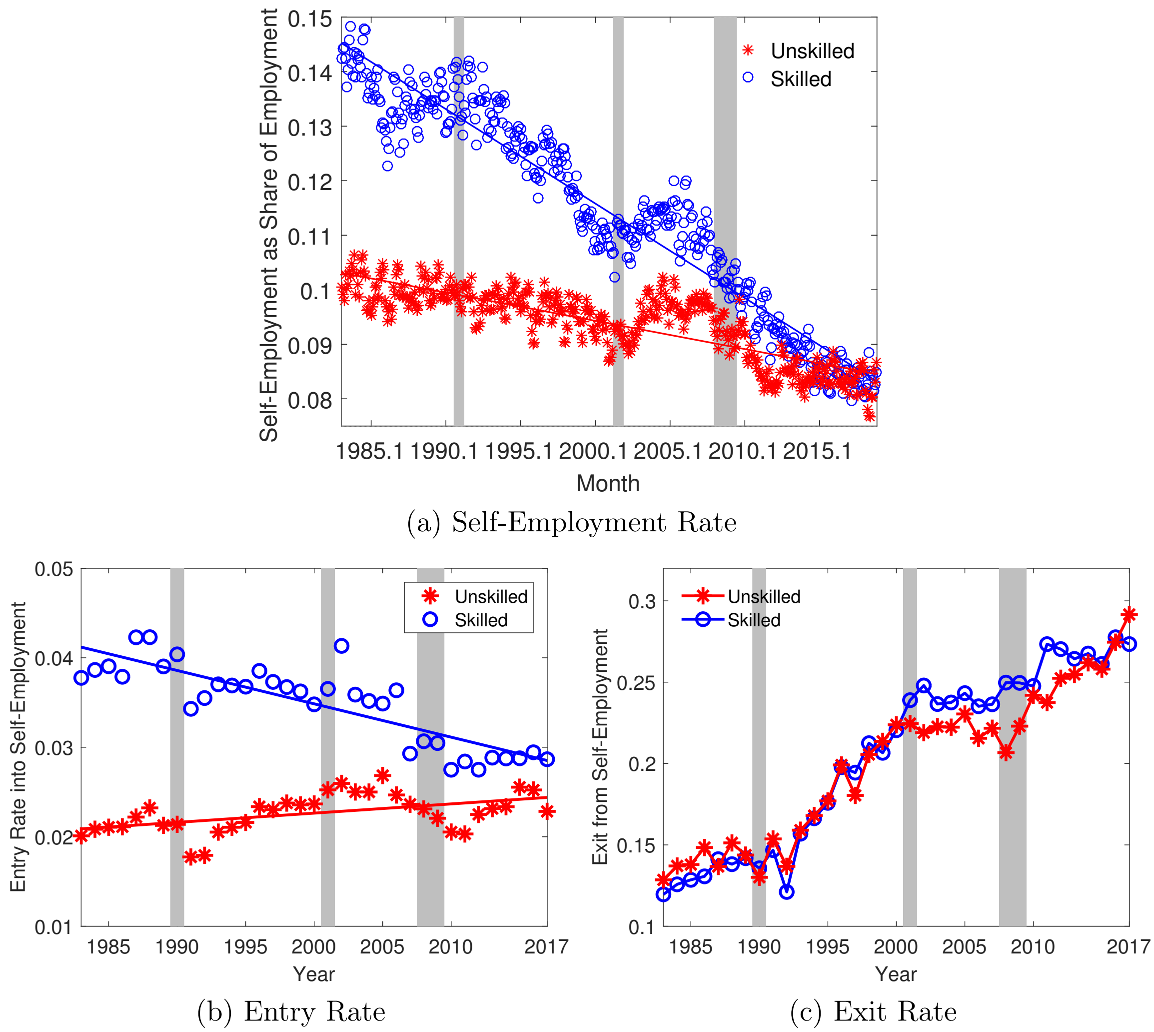
Figure 2.1c shows the converse of the entry rate; the exit rate out of self-employment.

[11] While this period overlaps with the 2003/4 CPS redesign we do not believe that it explains the trend reversal during this period. Indeed, among other phenomenon, this period also experienced dramatic increases in housing prices which may have provided sufficient wealth for some to become self-employed.

This figure plots the expected annual transition probability of a self-employed individual becoming an employee from 1983 to 2014. Notice first that the exit rate is an order of magnitude higher, for both population groups, than the entry rate and has increased during the sample period. This is intuitive given the decline in overall self-employment highlighted in figure 2.1a and the relatively flatter changes in exit rates. Similar to entry, the exit rate also illustrate a skill bias in their evolution but perhaps less dramatically so. In 1983, the exit rate was 15 and 18 percent for skilled and unskilled individuals respectively. By 2007 this figure was roughly the same for both groups, corresponding to a 67% and 53% increase for skilled and unskilled respectively. The exit rate continued to increased during and following the Great Recession and by 2014 had settled at 30 percent for both types of entrepreneur. As with the self-employment and entry rates, the exit rate did not monotonically increase over the

Taken together the panels in figure 2.1 show clear differences in the evolution of entry and exit, highlighting a pattern of skill biased decline in entrepreneurship.

Figure 2.1: Selection into and out of Self-Employment




Notes: Sample includes full-time, non-agricultural employees aged between 25 and 65 with at least a high school degree from the basic monthly CPS files. The self-employment rate is the share of the sample that is identified as self-employed. Additional details on these measures can be found in appendix 2.8.1. The shaded bars indicate recessions as determined by the NBER.

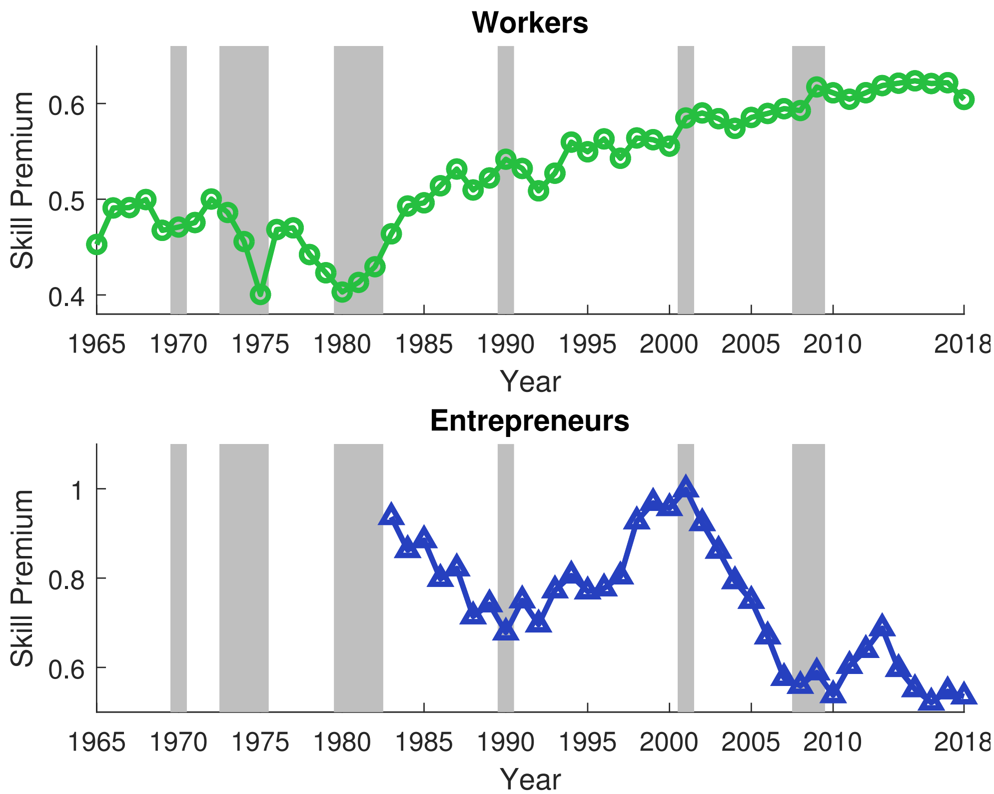
## 2.2.2 Skill Premium

An important factor in determining an occupational choice between employment and self-employment is the income earned in each occupation. Here we consider the income for both occupations across and within each skill group. Figure 2.2 summarizes the salient trends of interest regarding the relative price of skills for employees and entrepreneurs. That is the relative incomes across skill type and within occupation. While already well-studied we first consider the evolution of the skill premium of workers. This increased between 1965 and the early 70's before experiencing a decline to 1965 levels by 1980. Around the early 1980's the skill premium experienced a sharp increase until slowing down in the late 90's, all while continuing to increase throughout the last two decades. Indeed, at least since the early 80's, the relative price of skills have increased in spite of it's rising supply. This observation has motivated researchers to explore demand driven explanations for the changing wage structure and resultant inequality[12]. We rely only on skill biased technological change to deliver the time-varying skill premium and calibrate the model to match figure 2.2.

It is also necessary to consider the evolution of the skill premium of entrepreneurs. For instance if the skill premium of entrepreneurs grew faster than that for workers we would expect increased entry, lower exit and higher rates of self-employment. The second panel of figure 2.2 reports this measure. Firstly, notice that the skill premium for entrepreneurs is higher in levels than that for workers for most of the sample period since 1983. Secondly, the evolution of the returns to skills for entrepreneurs is starkly different from the steady increase observed for workers. While the premium has declined by 40% between 1983 and 2014 it has not done so monotonically. It fell through the 1980s up to the mid 1990s and again between 2001 and 2010. The two periods during which the premium consistently increased were between 1997 and 2001 and between 2010 and 2014. During these periods the annual average growth rate was 5.0% for the former and 4.9% for the latter. This is in contrast to the 0.6% and 1.6% increase, respectively, in the skill premium for workers over the same two periods. For the remaining sample period since 1983 the skill premium for workers has grown at a faster rate than that for entrepreneurs.

[12]See, for example, Card and DiNardo (2002), Cunha et al. (2011) and Burstein and Vogel (2016)

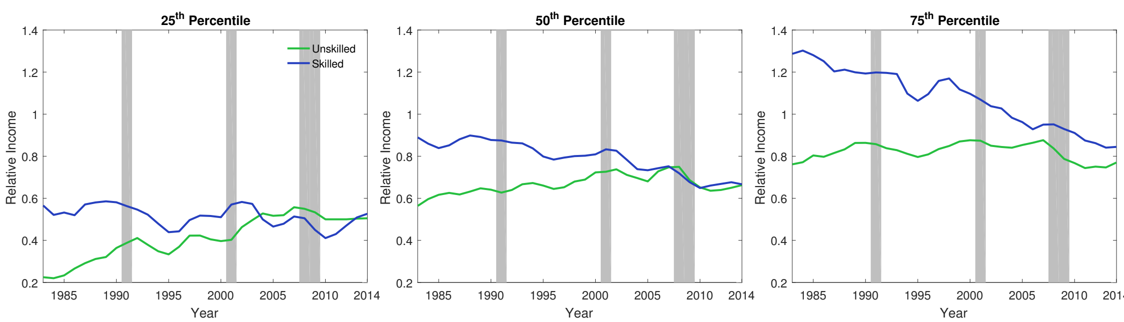
Figure 2.2: Skill Premium for Workers and Entrepreneurs




Notes: Sample includes full-time, non-agricultural employees aged between 25 and 65 with at least a high school degree from the March Supplement of the CPS. The IPUMS variables incwage and incbus are used as the measures of income for workers and entrepreneurs, respectively. The variable incbus is only available for both unincorporated and incorporated entrepreneurs starting 1983. The skill premium is the coefficient obtained from an OLS regression of log income on an indicator variable identifying those with at least a college degree (or 16 years of schooling). The skill premium for entrepreneurs is reported as a two year moving average. Entrepreneurs that report non-positive incomes are assumed to have log income equal to 0. The shaded bars indicate recessions as determined by the NBER. Additional details on the measurement of the skill premium can be found in appendix 2.8.

Figure 2.3 compares the incomes of worker and entrepreneurs within a skill group. In particular, the figure reports, for a given skill type, the ratio of incomes for entrepreneurs and workers at the first, second and third quartiles of their respective income distribution. Focusing first on level differences between skill groups, we observe the gap between skilled entrepreneurs and workers is generally larger than that between unskilled entrepreneurs and workers. Furthermore, this gap widens for both skill types as we move further up the income distribution. Notice, that the median entrepreneur earns less than the median worker for either skill type, a finding that is consistent with Hamilton (2000). Now focusing on the evolution of these ratios over time we observe that unskilled entrepreneurs and worker's incomes have grown at a relatively similar pace at each of the three points in the income distribution. However, skilled entrepreneurs incomes have *fallen* relative to skilled worker's incomes. This is an important finding as it reflects a change in the opportunity cost of self-employment for skilled individuals, a change that is not present for unskilled individuals. These findings are also consistent with the changes in skill premium for both occupations presented above.

Figure 2.3: Relative Incomes for Entrepreneurs and Workers



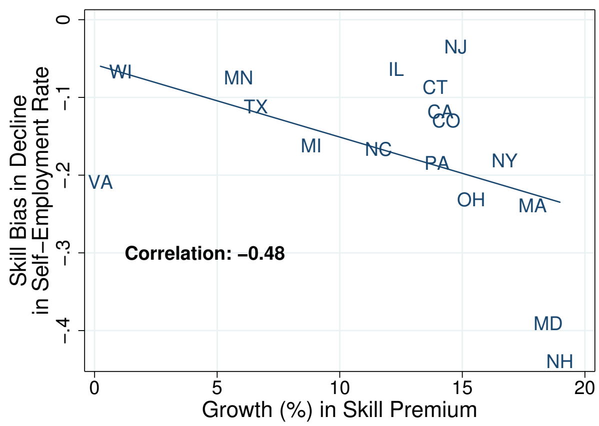

Notess: Sample includes full-time, non-agricultural employees aged between 25 and 65 with at least a high school degree from the March Supplement of the CPS. The IPUMS variables incwage and incbus are used as the measures of income for workers and entrepreneurs, respectively. The figure reports the ratio of entrepreneurial and worker income at a given point in their respective distribution for a given year and skill type. The shaded bars indicate recessions as determined by the NBER.

## 2.2.3 Cross-State Verification

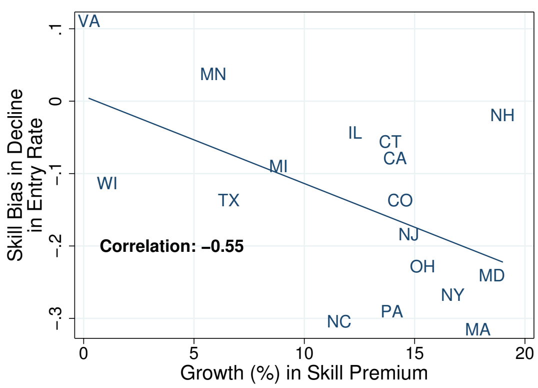
To provide support for a link between the rising skill premium of workers and the skill bias in entrepreneurial decline we exploit variation in these two measures across states. To account for the smaller sample sizes at the state level the data is pooled into two year bins which include data from 1983-95 and 1996-2005. Using the pooled data, we find that those states which experienced faster growth in the skill premium also experienced a higher degree of skill bias in measures of entrepreneurship. The latter measure is constructed by first computing the self-employment, entry and exit rates for each state by skill type. Then we compute the growth rates in each of the three measures; the degree of skill bias in entrepreneurial decline is simply the difference between growth rates for skilled and unskilled individuals. For example, if the entry rate for skilled individuals fell by 5% and for unskilled individuals rose by 10% then the degree of skill bias in the decline in entry rate is the difference between the two or -0.15.

Panels (a) and (b) of figure 2.4 plot the skill bias in the decline in self-employment and entry rate, respectively, against the growth in skill premium. They illustrate a significant positive correlation between the growth in the skill premium and the skill bias in entrepreneurial decline. Furthermore, panel (a) highlights the broad nature of the skill bias in entrepreneurial decline with skilled individuals in all states experiencing a steeper decline in the self-employment rate than unskilled individuals. The same is true for the entry rate with the exception of Virginia and Minnesota where both states experienced the opposite. Panel (c) complements these findings by studying the skill bias in the increase in exit rate. Unlike self-employment and entry the exit rate, for many states, experienced an almost skill neutral change over the two year bins. Despite this we do observe a weak positive correlation between the growth in skill premium and the skill bias in exit rate.

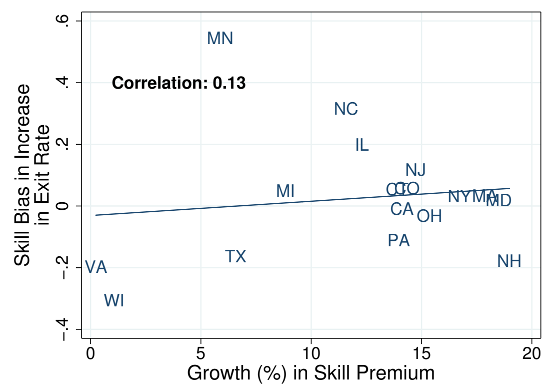
Figure 2.4: State Level Variation in Worker Skill Premium and Skill Biased Entrepreneurial Decline




(a) Self-Employment Rate




(b) Entry Rate




(c) Exit Rate

Notes: The growth in the skill premium is the percentage change in the skill premium for the pooled years 1983-1995 and 1996-2007 as measured in the March CPS sample. The measurement of the skill bias in the change of self-employment, entry and exit rates in explained in detail in appendix 2.8.1. For the self-employment and entry rates values below zero indicate a higher degree of skill biased decline in overall and entry into entrepreneurship. For the exit rate values above zero denote a higher degree of skill biased increase in the exit rate into entrepreneurship. The reported slope and coefficient are obtained from an OLS regression, the parentheses include the associated $p$-values from this regression. A total of 17 states are analyzed and they include; California, Colorado, Connecticut, Illinois, Maryland, Massachusetts, Michigan, Minnesota, New Hampshire, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Texas, Virginia and Wisconsin. Only those states that constitute at least 1.5% of the observations in the March CPS data from 1983 to 2007 are included. Additionally, those states ( Florida, Georgia and Iowa) that experienced a decline in the skill premium between 1983-1995 and 1996-2007 are excluded.

Taken together figure 2.4 shows a correlation between the differential decline in entrepreneurship by skill type and the rising worker skill premium. While we cannot determine causality from this figure we take this to be evidence in support of our modeling decision to the latter phenomenon driving the former.

### 2.2.4 Entrepreneurial Polarization

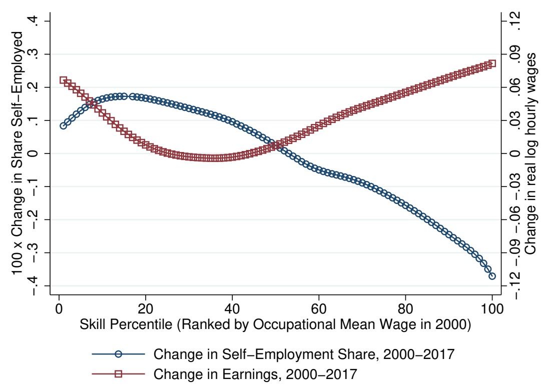
So far, we have focused on the differential wage growth between two broadly defined groups; skilled and unskilled individuals. However, recent work (e.g. David and Dorn (2013)) has argued that wage growth has been non-monotonic across the skill distribution, with middle skilled workers experienced relatively slower growth in earnings - wage polarization. Given this, we posit that entrepreneurship should have experienced larger declines for skill groups whose incomes rose faster - consistent with our intuition thus far. Here, we test this intuition by studying whether the wage polarization emphasized in recent work has also resulted in entrepreneurial polarization.

We perform two exercises. First, we use data from the American Community Survey (ACS) to rank occupations from highest to lowest paid wages. We will use this ranking as a measure of the skill required for an occupation and then study the changes in the share of entrepreneurs that report working in occupations over time. This measures the change in the *share of self-employed* by skill percentile. Second, we ask whether there was polarization in the entry into entrepreneurship. Using the same occupational ranking as a measure of skill, we consider the sample of newly self-employed in the CPS, that is those that transitioned from employment into entrepreneurship. We then compute the share of entrants based on the occupation that they were previously employed in as workers and study changes in this measure by skill percentile. This measures the change in *entry into self-employment* by skill percentile. Details on the data construction is included in the appendix.

Figure 2.5 shows the change in share of self-employed as well as changes in worker's wages between the reference year of 2000 and 2005, and 2017. Focusing first on the changes in income; the figure shows relatively slower income growth for middle skilled entrepreneurs relative to low and high skilled workers. Importantly, this wage polarization appears to be reflected in the share of self-employed with entrepreneurs from the middle of the skill distribution exhibiting a slower decline than those from either the high and low end of the distribution.

Figure 2.5: Smoothed Changes in Self-Employment and Real Wages by Skill Percentile


(a) Changes between 2000 and 2005




(b) Changes between 2000 and 2017

Notes: The horizontal axis reports the skill percentile of occupations ranked by the mean earnings in 2000. The left axis reports 100 times the difference in share of self-employed in an occupation. The right vertical axis reports the change in log real hourly wages in an occupation. Self-employment shares are calculated using ACS weights and are the weeks worked times the usual weekly hours worked in the prior year. Hourly wage data is measured as the ratio of annual earnings, and the product of weeks and usual hours worked. The underlying data is smoothed using locally weighted scatterplot smoothing (LOWESS) with bins of size 0.8. Data is from the 2000, 2005 and 2017 ACS. We follow David and Dorn (2013) in constructing a consistent sample of occupations over time.

While figure 2.5 is suggestive, smoothing the underlying data obscures the heterogeneity in wage growth and self-employed across skill percentiles. We perform a more robust test of polarization by testing for a quadratic fit of the data, as in Goos and Manning (2007). More specifically, we estimate the following regression:

$$\Delta y_j = \alpha + \beta j + \gamma j^2 \tag{2.1}$$

where $j \in \{1, 2 \ldots, 100]$ is the skill percentile and $\Delta y$ is the change in log hourly real wages and share of self-employed. If changes in the share of self-employed mirror changes in wages, we should expect opposite signs on the coefficients $\beta$ and $\gamma$. Table 2.1 reports these coefficients.

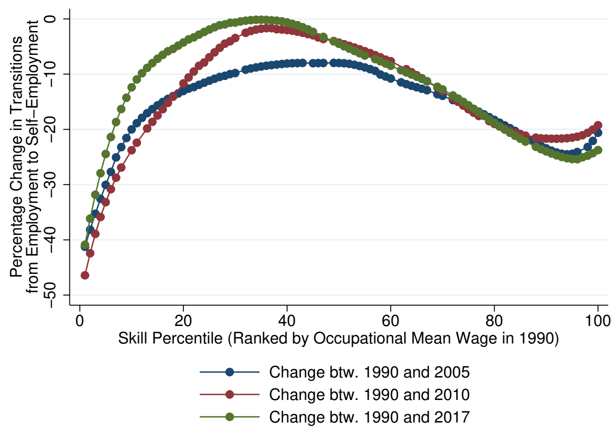
Table 2.1: Comparing Polarization in Wages and Entrepreneurship

| | 2000-2005 | | 2000-2017 | |
|---|---|---|---|---|
| | Δ Wages | Δ Self-Employed | Δ Wages | Δ Self-Employed |
| Percentile | -0.0024 | 0.0076* | -0.0066 | 0.0013 |
| | (0.0050) | (0.0042) | (0.0055) | (0.0079) |
| Percentile Sq. | 0.0000 | -0.0001** | 0.0001 | -0.0001 |
| | (0.0000) | (0.0000) | (0.0001) | (0.0001) |
| N | 100 | 100 | 100 | 100 |
| $R^2$ | 0.0041 | 0.0469 | 0.0155 | 0.0828 |

*Notes:* * and ** indicate statistical significance at the 10 and 5 % level respectively.

First, we do not find robust evidence for wage polarization; the linear and quadratic coefficients have the correct sign but are not statistically significant. This is consistent with recent work by Böhm (2018). Our focus is not on the existence of wage polarization but rather whether the changes in the income structure of workers are mirrored by changes in the overall share of self-employed. As shown in table 2.1, the linear and quadratic coefficients on changes in self-employment have the *opposite* sign to those for wage changes and statistically significant between 2000 and 2005. These results suggest that the share of self-employed in high and low skill occupations declined relative to the those with intermediary skills during the same time that wages for high and low skilled workers were rising faster than those for middle skilled workers. This is consistent with our theory and results thus far for the broader groups of skilled and unskilled workers and the associated changes in the worker skill premium. However, there are several caveats to this analysis. First, the occupations reported by entrepreneurs may not accurately reflect their an individual's skill level. For example, a former financial manager operating a restaurant may report themselves as being in a personal services occupation while their skill level, as inferred from their previous occupation may be higher. Second, since the ACS does not include unincorporated self-employed prior to 2000, our analysis is restricted to relatively short time period. To overcome these limitations, we use data from the CPS and consider entry into entrepreneurship and measure changes in this measure based on the previous occupation (as an employee), of the newly self-employed.[13]

Figure 2.6: Smoothed Changes in Entry into Self-Employment by Skill Percentile in Employment




Notes: The horizontal axis reports the skill percentile of occupations ranked by the mean earnings in 1990 using ACS data on employees. The vertical axis reports the percentage change in entry into self-employment relative to share of employment for a give occupation. Self-employment shares are calculated using matched CPS while employment shares are calculated using ACS data.. Additional details are included in the appendix. The underlying data is smoothed using locally weighted scatterplot smoothing (LOWESS) with bins of size 0.8. Data on employment shares the 2005, 2010, 2017 ACS while information on . We follow David and Dorn (2013) in constructing a consistent sample of occupations over time.

[13]Notice that comparing the share of entrants by previous occupation in employment, over time, will also include changes in the underlying share of occupations in employment that have occurred over time (i.e. job polarization). Since we are only interested in measuring changes in propensities for entry into entrepreneurship by occupation, we divide the share of newly self-employed by the share of employees in each occupation and report changes in this ratio over time. Details are included in the appendix.

Figure 2.6 reports the percentage change in transitions into self-employment across skill percentiles for three reference years 2005, 2010 and 2017 relative to the base year of 1990. The figure displays roughly an inverted U-shape for each of the three reference years considered with larger declines in entry for those at the right and left tails of the skills distribution relative to those in the middle. As with changes in overall self-employment, we test for a quadratic fit of the underlying data using specification 2.1 and report the results in table 2.2. While statistically insignificant, the linear and quadratic term coefficients are positive and negative, respectively. This is consistent with the results for changes in the share of entrepreneurship and is suggestive of a polarization in entrepreneurship that is exactly opposite to that observed in wages.

Table 2.2: Testing for Polarization in Entry into Entrepreneurship

| | $\Delta_{90-05}$ | $\Delta_{90-10}$ | $\Delta_{90-17}$ |
|---|---|---|---|
| Percentile | 0.9575 | 1.4199 | 0.9933 |
| | (0.8591) | (0.8924) | (0.8237) |
| Percentile Sq. | -0.0100 | -0.0144* | -0.0117 |
| | (0.0083) | (0.0085) | (0.0079) |
| | | | |
| N | 93 | 89 | 93 |
| $R^2$ | 0.0162 | 0.0332 | 0.0329 |

Taken together, the evidence in this section suggests that the changes in entrepreneurship is negatively correlated with wage changes of employees, findings that are intuitively consistent with the hypothesis that changes in the income structure may have an important role in driving the decline in entrepreneurship.

## 2.3 Robustness

In this section we perform a series of robustness exercises on the findings relating to the decline in entrepreneurship. We begin by addressing two main drawbacks to using the CPS monthly files. Firstly, the monthly CPS data do not include detailed information on income and wealth. Although we exclude those engaged in part-time activities, a measure of income could be used to determine whether an occupation, particularly self-employment, is casual. Additionally, as wealth is an important determinant in entry into self-employment it is important to control for it in our analysis.[14] A second drawback of the monthly CPS files is a lack of data on firm size. The literature on the decline in startups has focused primarily on employers[15] and it is not possible to distinguish between employers and non-employers using the monthly files. To ensure that our results are robust to excluding non-employers and casual business owners we repeat our analysis using the March supplement of the CPS which includes measures of income and firm size. We also consider alternative data definitions and study analogous evidence using the Survey of Income and Program Participation (SIPP).

### 2.3.1 March CPS and SIPP Data

Table 2.3 shows the overall, entry and exit rate into self-employment for the March CPS and SIPP data from 1996 onward. Since we are able to observe incomes in both these data we restrict the sample to only include those individuals that earn at least 5000 2010USD in their occupation. This restriction ensures that we only consider transitions across occupations that are not casual. Furthermore, since data on respondents of the SIPP is available at the monthly frequency we are not bound to consider annual entry and exit rates. Indeed, this data allows us to impose stricter restrictions to identify genuine transitions to an from self-employment. As such, employees in the SIPP are said to have transitioned into self-employment if they are employed for at least a quarter and then in the following quarter identify as being self-employment for at least two months. The findings using these data and restriction are consistent with a skill biased decline in entrepreneurship.

[14] See for example Cagetti and De Nardi (2006).

[15] A common data source is the Business Dynamics Statistics (BDS) and is used in for example Decker et al. (2013)

Table 2.3: Evidence from the SIPP and March CPS

Panel A: **March CPS Sample**

| Years | **Self-Employment Rate** | | **Entry Rate** | | **Exit Rate** | |
|---|---|---|---|---|---|---|
| | Unskilled | Skilled | Unskilled | Skilled | Unskilled | Skilled |
| 1996-2000 | 0.065 | 0.062 | 0.017 | 0.022 | 0.27 | 0.30 |
| 2001-2006 | 0.070 | 0.059 | 0.015 | 0.020 | 0.28 | 0.34 |
| 2007-2014 | 0.063 | 0.056 | 0.017 | 0.019 | 0.34 | 0.37 |

Panel B: **SIPP Sample**

| Panel Years | **Self-Employment Rate** | | **Entry Rate** | | **Exit Rate** | |
|---|---|---|---|---|---|---|
| | Unskilled | Skilled | Unskilled | Skilled | Unskilled | Skilled |
| 1996-99 | 0.085 | 0.099 | 0.016 | 0.019 | 0.107 | 0.121 |
| 2001-03 | 0.091 | 0.106 | 0.016 | 0.017 | 0.112 | 0.126 |
| 2004-07 | 0.076 | 0.091 | 0.013 | 0.014 | 0.105 | 0.121 |
| 2008 -13 | 0.070 | 0.080 | 0.014 | 0.016 | 0.107 | 0.114 |

*Notes*: Both March CPS and SIPP amples includes full-time, non-agricultural employees or self-employed individuals aged between 25 and 65 with at least a high school degree and annual earnings of 5,000 2010USD. The March CPS data is pooled for the year bins specified and the SIPP data is for a given wave following 1996.

### 2.3.2 Incorporated, Unincorporated, and Older Population

Table 2.4 reports the percentage change in overall, entry and exit rates of self-employment for all self-employed, incorporated self-employed and those between the age of 45 and 65. Including only the incorporated self-employed is an important restriction as these entrepreneurs are more likely to be employers and earn higher returns as highlighted in Hipple and Hammond (2016) and Levine and Rubinstein (2016). Considering only transitions to and from incorporated self-employment also exhibits a skill bias in overall, entry and exit rates. However, unlike the sample which includes both unincorporated and incorporated self-employed the entry rate into incorporated self-employment for both skilled and unskilled individuals increases between 1983 and 2006. However, as is consistent with the full sample this increase is flatter for skilled individuals.

Restricting the sample to include only older individuals accounts for the possibility that younger individuals are more likely to be financially constrained and less likely to enter into entrepreneurship[16]. As shown in the last two columns of table 2.4 older individuals also featured a skill biased decline in entrepreneurship.

Table 2.4: Percentage Change in Self-Employment, Entry and Exit Rate over time.

Panel A: **Self-Employment Rate**

| | **All Self-Employed** | | **Incorporated** | | **45 - 65 Year Olds** | |
|---|---|---|---|---|---|---|
| | Unskilled | Skilled | Unskilled | Skilled | Unskilled | Skilled |
| 1983-90 | -2.8 | -6.2 | -0.6 | -4.2 | 0.7 | -3.2 |
| 1990-2000 | -7.6 | -17.0 | 5.1 | -9.6 | -14.2 | -22.3 |
| 2000-06 | 5.3 | 0.2 | 13.0 | 6.7 | 1.2 | -1.0 |
| 2006-2014 | -14.4 | -20.7 | -3.4 | -16.7 | -11.5 | -17.5 |
| **1983-2014** | **-19.1** | **-38.1** | **14.0** | **-23.1** | **-22.6** | **-38.5** |

Panel B: **Entry Rate**

| | **All Self-Employed** | | **Incorporated** | | **45 - 65 Year Olds** | |
|---|---|---|---|---|---|---|
| | Unskilled | Skilled | Unskilled | Skilled | Unskilled | Skilled |
| 1983-90 | 3.2 | -2.6 | 2.9 | -0.5 | 7.0 | 19.8 |
| 1990-2000 | 10.9 | -4.1 | 24.7 | 9.5 | 18.1 | -10.4 |
| 2000-06 | 2.9 | -4.7 | 14.2 | -2.1 | -4.2 | -4.0 |
| 2006-2014 | -7.4 | -15.2 | 2.2 | -12.7 | -5.1 | -13.3 |
| **1983-2014** | **9.0** | **-24.6** | **49.8** | **-7.0** | **14.9** | **-10.6** |

Panel C: **Exit Rate**

| | **All Self-Employed** | | **Incorporated** | | **45 - 65 Year Olds** | |
|---|---|---|---|---|---|---|
| | Unskilled | Skilled | Unskilled | Skilled | Unskilled | Skilled |
| 1983-90 | 8.2 | 14.8 | 4.5 | 13.2 | 5.2 | 26.5 |
| 1990-2000 | 42.9 | 43.6 | 42.9 | 57.5 | 71.4 | 57.9 |
| 2000-06 | -4.5 | 6.3 | -3.7 | -0.5 | -7.7 | 5.6 |
| 2006-2014 | 12.7 | 11.9 | 9.1 | 11.1 | 14.8 | 14.4 |
| **1983-2014** | **66.5** | **96.3** | **57.0** | **97.1** | **91.2** | **141.3** |

*Notes*: Data is from the monthly CPS files and the **All Self-Employed** sample includes full-time, non-agricultural employees and entrepreneurs aged between 25 and 65 with at least a high school degree and is identical to the data presented in figure 2.1. **Incorporated** includes only those entrepreneurs who either transitioned to or from incorporated self-employed under the same sample restrictions. **45-65 Year Olds** restricts the **All Self-Employed** sample to include only those between the ages of 45 and 65.

## 2.4 Model

The model economy is populated with a unit mass of agents that are heterogeneous in two dimensions; ability as an employee and ability as an entrepreneur denoted by $a$ and $z$ respectively. The joint distribution of employee and entrepreneurial ability is then given

[16]See for example Huggett (1996) for the evolution of wealth over the life-cycle. Hurst and Lusardi (2004) for evidence linking entry into entrepreneurship and wealth.

by$\tilde{F}(a, z)$. We assume that ability as an employee can take on only two values denoting skilled ($a = s$) or unskilled ($a = u$) agents. Entrepreneurial ability has a continuous support, a la and follows a distribution $F_a(z)$ for $a \in \{s, u\}$[17]. Notice, that we allow for entrepreneurial ability to be dependent on ability as an employee this allows for the possibility that skilled employees may also be skilled entrepreneurs and in our calibration we do find this to be the case. The only decision faced by agents is their occupational choice. As a worker, agents supply one unit of labor in-elastically and gets a fixed wage ($w_a$) depending on their skill type. As entrepreneurs, agents have access to a CES production function and choose to hire skilled and unskilled workers. This model is simple generalization of Lucas (1978) with heterogeneity in two dimensions; employee and managerial ability.

### 2.4.1 Production Function

The production function for an entrepreneur of ability $z$ is given by:

$$Y(z) = z\left[\theta\left(A_s L_s\right)^{\sigma} + (1-\theta)\left(A_u L_u\right)^{\sigma}\right]^{\frac{\eta}{\sigma}}$$

We rewrite the production function as:

$$Y(z) = \boldsymbol{A} z\left[\Theta_s L_s^{\sigma} + L_u^{\sigma}\right]^{\frac{\eta}{\sigma}}$$

where $\boldsymbol{A} \equiv (A_u^{\sigma}(1-\theta))^{\frac{\eta}{\sigma}}$ and $\Theta_s \equiv \left(\frac{\theta}{1-\theta}\left(\frac{A_s}{A_u}\right)^{\sigma}\right)$.

The entrepreneur then solves the following problem:

$$\pi(z) = \max_{\{L_s, L_u\}} Y(z) - w_s L_s - w_u L_u \tag{2.2}$$

[17]The joint distribution is then given by $\tilde{F}(a, z) = \bigcup_a F_a(z)$.

### 2.4.2 Occupational Choice

We assume that agents live for a single period and focus only on the static version of the occupational choice. Hence the only decision that needs to be made by workers is to pick their occupation $o(a, z)$ by comparing the one-period returns in each:

$$o(a,z) = \begin{cases} 0 & \text{if } w_a \geq \pi(z) \\ 1 & \text{if } w_a < \pi(z) \end{cases}$$

### 2.4.3 Equilibrium

We now characterize the equilibrium in the static model, which can be summarized by prices ($w_s$,$w_u$ ) and occupational choice function $o(a, z)$ for each agent such that :

1. Agents make the optimal occupational choice
2. Labor Markets clear

The occupation choice function features a threshold of entrepreneurial ability $\bar{z_a}$ above which type $a$ agents become entrepreneurs and below which they become workers[18]. Given this threshold property of the function $o(a, z)$ both skilled and unskilled labor market clearing conditions are given by:

$$\lambda F_s(\bar{z_s}) = \int_{\bar{z_s}}^{\infty} \lambda L_s(z, w_u, w_s)\ dF_s(z) + \int_{\bar{z_u}}^{\infty} (1-\lambda) L_s(z, w_u, w_s)\ dF_u(z) \tag{2.3}$$

[18]The occupation choice cutoffs solve the following equations:

$$\pi(\bar{z_s}) = w_s \text{ and } \pi(\bar{z_u}) = w_u$$

$$(1-\lambda)F_u(\bar{z_u}) = \int_{\bar{z_s}}^{\infty} \lambda L_u(z, w_u, w_s)\ dF_s(z) + \int_{\bar{z_u}}^{\infty} (1-\lambda) L_u(z, w_u, w_s)\ dF_u(z) \tag{2.4}$$

where the share of the population that is skilled is given by $\lambda$ the unskilled by $1-\lambda$.

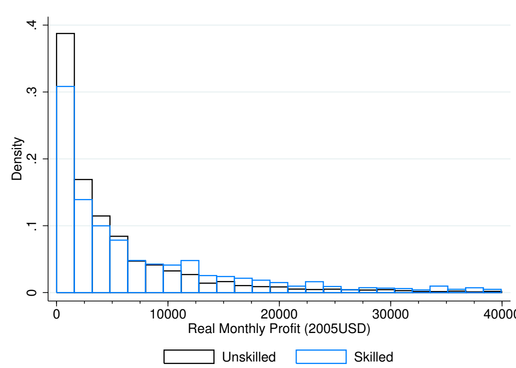
The left-hand-side of equation 2.3 (equation 2.4) is the total mass of skilled (unskilled) agents who choose to become workers, and that population should be equal to the sum of those hired by the skilled entrepreneurs and those hired by the unskilled entrepreneurs, which are exactly represented by the two terms on the right-hand-side of the equation. We assume that entrepreneurial ability follows the Pareto distribution, which allows us to solve the static model analytically as shown in appendix 2.9.

## 2.5 Calibration

There are a total of seven parameters that will need to be pinned down summarized in the vector $(\sigma, \eta, \lambda_t, \xi_s, \xi_u, \Theta_{s,t}, \boldsymbol{A}_t)$. Three parameters will be taken directly from the data or the literature: $\sigma, \eta, \lambda_t$. The share of the population that is high skilled, $\lambda$ is taken directly from the Current Population Survey (CPS) and is given by the share of the U.S. population aged between 25 and 65 years old at least with a college degree. The remainder, $1-\lambda$ is the mass of low skilled workers which varies over time. The elasticity of substitution $\sigma$ and span of control parameter $\eta$ are fixed over time and will be determined from the literature. This leaves four parameters $\Gamma_t = (\xi_s, \xi_u, \Theta_{s,t}, \boldsymbol{A}_t)$ that will need to be jointly calibrated to match moments in the data.

**Tail Parameter** $\xi_a$ The tail parameter of entrepreneurial skills is chosen to fit the empirical distribution of entrepreneurial earnings. From the first order conditions of the mode we know that $\pi(z) \propto z$. This suggests that the distribution of observed incomes for entrepreneurs in the data is also Pareto in particular the distribution of the top earners. So we choose $\xi_a$ to match the entrepreneurial profit distribution of the top 75% of earners with ability $a$. Since $\xi_a$ is to be fixed over time we can choose pool years of data together and use measures of real earnings. Controlling for observable is not necessarily an option since a standard OLS regression will yield that the residual earnings are normally distributed. So instead we can justify using real earnings figures by assuming that the observables are evenly distributed along agents of ability $a = s$ and $a = u$. Figure 2.7 shows the profit distribution of the top 75% of income earners in the pooled SIPP panels of 1996, 2001, 2004, and 2008. It is clear that $\xi_s < \xi_u$ and that the Pareto distribution is a good approximation. Following Axtell (2001) we use two alternate measures of earnings i) Profit ii) Income. We include only the top 75% of earners. Table shows the estimated tail parameters using these two measures for the sample of all entrepreneurs and the sample of those entrepreneurs who are operating a business that is at most two years old. The preferred estimates of $\xi_a$ are obtained by using income as the measure of earnings and considering only the sample of new entrepreneurs which suggests that $\xi_s = 1.284$ and $\xi_u = 1.435$. We rescale both tail parameters to make sure the numerical solution exists, i.e., we choose $\xi_s = 6.5$ and $\xi_u = 6.5 \times \dfrac{1.435}{1.284}$. The support for both distributions if $[1, \infty)$.

Figure 2.7: Density of Entrepreneurial Earnings in the Pooled SIPP



**Productivity $A_t$ and $\Theta_{s,t}$** The time varying values of the skill-neutral productivity $A_t$ are chosen to match model-generated output with real Gross Domestic Product (GDP) in the United States. The skilled labor augmenting productivity $\Theta_{s,t}$ is pinned down by matching the U.S. worker skill premium. Table 2.5 summarizes the model parameters and targets for calibration.

Table 2.5: Model Parameters

| Parameter | Description | Source/Moment Targetted |
|---|---|---|
| $\sigma = 0.3$ | Elasticity of Substitution | Katz and Murphy (1992) |
| $\eta = 0.8$ | Span of Control | Midrigan and Xu (2010) |
| $\lambda_t$ | Share of High Skill Agents | Share of College Grads in U.S. (aged 25-65) |
| $\xi_u = 6.5, \xi_s = 7.2644$ | Pareto Tail | Earnings Dist. of Entrep. in SIPP |
| $\Theta_{s,t}$ | Skilled Labor Augmenting Productivity | Worker Skill Premium |
| $A_t$ | Skill-neutral Productivity | Real GDP |

## 2.6 Results

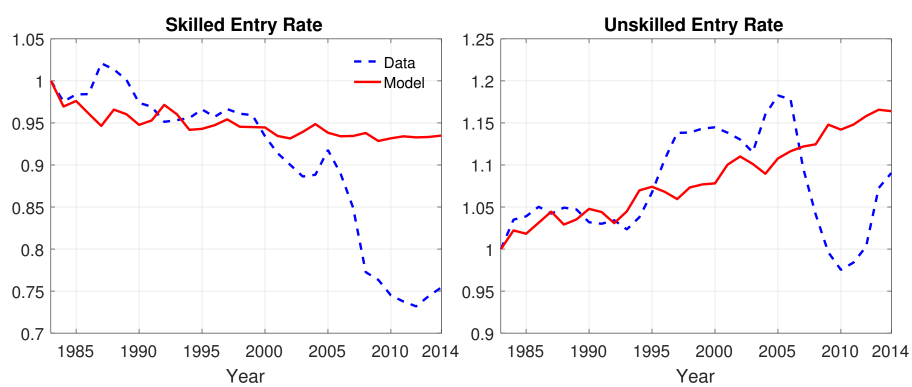
Our simple, static framework does not feature any dynamics, and hence we are not able to create model counterparts of the overall and exit rates of entrepreneurship. Instead, we impose that the entry rate, $E_{a,t}$ is the share of entrepreneurs in the population for each employee skill type $a$. Given our distributional assumptions the entry rate is given by:

$$E_{a,t} = F_a(\bar{z}_a) = \left(\frac{1}{\bar{z}_a}\right)^{\xi_a} \quad \text{for } a \in \{s, u\}$$

The aggregate entry rate is simply the weighted average for both employee skill types, $E_t = \lambda_t E_{s,t} + (1 - \lambda_t) E_{u,t}$.

Figure 2.8 compares the model predicted entry rate to the data for both the skilled and unskilled individuals. For either skill type and prior to the Great Recession the model provides a good fit for the evolution of entry rates. The inability for this simple framework to match entry rates during and after the Great Recession is not surprising as the only parameter that captures aggregate economics conditions, $\mathbf{A}$, is neutral across occupations and skill types. To match the dramatic drop in entry rates during the Great Recession the model requires a change that is biased towards entrepreneurs as emphasized in recent work [19]. Instead we will focus on the period just prior to the Great Recession; 1983 to 2006. We normalize the model and data entry rate to 1983 levels. For both skilled and unskilled individuals the model is able to track the trend in entry rates. The observed change in entry rates between 1983 and 2006 for skilled and unskilled individuals was -11.0% and 17.8%, respectively. The simulated change during this period is -6.6% and 11.6% respectively. This suggests that skill-biased technical change and the accompanying rise in worker skill premium can account for around one-third of the change in entry rates for skilled and unskilled individuals over this period.

Figure 2.8: Model and Data Entry Rates relative to 1983 levels




The model also has implications for the entrepreneurial skill premium. We compare the median entrepreneurial earnings in each skill group and use that as our measure of the skill

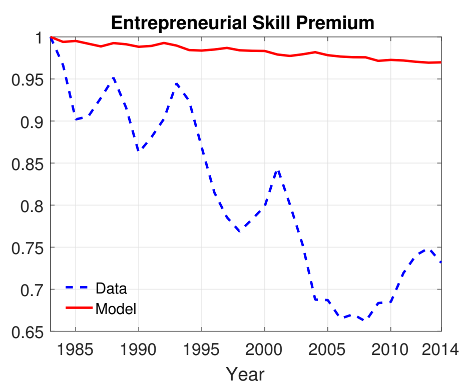
[19] Buera et al. (2015) and Siemer (2016) highlights the impact of the Great Recession on tightening financial constraints, which are particularly important for existing and potential entrepreneurs.

premium. Given the assumption of an unbounded Pareto distribution we show that this skill premium $SP_{e,t}$ is simply:

$$SP_{e,t} = \frac{\bar{z_{s,t}}}{\bar{z_{u,t}}}$$

Figure 2.9 compares this measure in model to it's empirical counterpart. As with the entry rates the model is able to track the direction of the skill premium, however it cannot match the magnitudes. Between 1983 and 2006 the observed entrepreneurial skill premium fell by 34% while the model predicts only a 2.5% decline. This accounts for only 6% of the observed decline. This suggests that the workers skill premium plays only a minor role in driving the change in entrepreneurial skill premium and emphasizes the need for a more full-fledged model to jointly explain the changing income structure and the skill biased decline in entrepreneurship.

Figure 2.9: Model and Data Entrepreneurial Skill Premium




Notes: Sample includes full-time, non-agricultural employees aged between 25 and 65 with at least a high school degree from the March supplement of the CPS. The IPUMS variables incbus is used as the measures of income for entrepreneurs. The skill premium is The entrepreneurial skill premium is the ratio of median earnings for skilled and unskilled entrepreneurs.

## 2.7 Conclusion

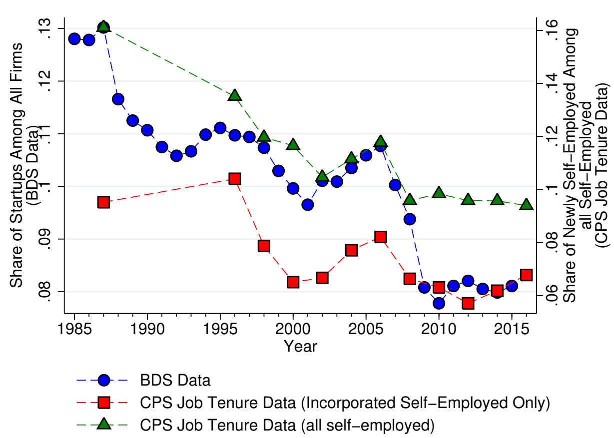
Much research has been conducted in documenting and understanding the decline in firm entry in the US. While existing work has focused on the aggregate entry rate, this paper presents the first evidence showing that this decline in entry is not shared uniformly across skill groups. This is an important dimension to understand since skilled individuals tend to form more successful businesses. Motivated by this skill bias in entrepreneurial decline we study worker and entrepreneurial income structure over time and argue that this can help understand our findings regarding entry. The simple static model we present provides some support for a role of skilled biased technological change in driving this skill biased decline in entrepreneurship and focuses only on the worker skill premium. However, this model lacks the richness needed to match the complete set of empirical findings in this paper and related literature. Endogenizing worker skill premium and matching the growth of incumbents as well as the changing income structure of entrepreneurs are all areas that we intend on incorporating in future work.

## 2.8 Data Appendix (Not intended for publication)

### 2.8.1 CPS Data

Most of the current literature documenting the evolution of firm entry and dynamism employs firm-level data. We begin by first assessing the suitability of using the individual level CPS data to relates to outcomes from firm level data. Figure 2.10 plots the startup rate using data from both the Business Dynamics Statistics (BDS) and the CPS Job Tenure Supplement. The BDS is a database of the universe of employer firms and has been frequently used to document the decline in startups. The CPS Job Tenure Supplement has been conducted periodically since 1987 and is advantageous as it asks self-employed individuals the length of time that they have been engaged in self-employment. The figure plots the startup rate - the share of young (less than one years old) firms/entrepreneurs amongst all firms/entrepreneurs and shows that, while there are level differences, the CPS startup rate tracks closely the time path of the startup rate in the BDS. This provides confidence in our use of the CPS data in understanding and relating to the firm level evidence in the existing literature.

Figure 2.10: Startup Rate in BDS and CPS




Notes: The figure plots startups, defined as firm or entrepreneurs that have been in operation for under a year, as a share of all firms or entrepreneurs. Data from the CPS Job Supplement employs that same sample restrictions are those in the CPS monthly sample.

#### Basic Monthly Surveys

**Matching Respondents** Participants in the CPS are interviewed at most 8 times over a period of 16 months. The rotating panel is designed to survey individuals for 4 consecutive months, then they are not interviewed for 8 months, and they return for a final 4 months. This design allows us to match individuals across interviews either by months of by year. We link individuals across a calendar year. That is, we match responses from interview $n$ to interview $n + 4$ in the same month the following year for $n \in \{1, 2, 3, 4\}$. Whenever possible, matches from all $n$ interviews are including so the same individual will be including in the final sample at most four times in four different calendar months. Using only a single interview pair, i.e.$(n, n + 4)$ for some $n$, to match individuals yields qualitatively similar results but significantly decreases the sample size. The average match rate between interviews is around 67% and the final sample includes 6.1 million matched interviews from 2.3 million unique individuals. See Rivera Drew et al. (2014) for additional details on linking respondents using the IPUMS CPS monthly files.

**Estimating Entry and Exit Rates** To construct our measure of entry rate we assign a binary variable $d_{i,s,y}$ to each individual $i$ in our sample which is equal to 1 if a wage worker of skill types$s$ transitions to entrepreneurship in year $y+1$ and 0 otherwise. We then perform a probit regression on $d_{i,s,y}$ for a given skill type $s$ controlling for the following: gender, race, marital status, census region, metro area status. We also include a quartic in age, year dummies and 2 digit industry and occupation controls as a wage worker in year $y$. The occupation categories are at the 2-digit level and are constructed following David and Dorn (2013). We then use the predicted values from this regression $\hat{d}_{i,s,y}$ and report the average across all individuals for a given year; $\mathbb{E}_i(\hat{d}_{s,y,i})$. Including controls industry and occupation in year $y + 1$ yields similar results. The construction of the exit rates is analogous with the binary variable instead identifying transitions from self-employed in year $y$ to employment in year $y + 1$.

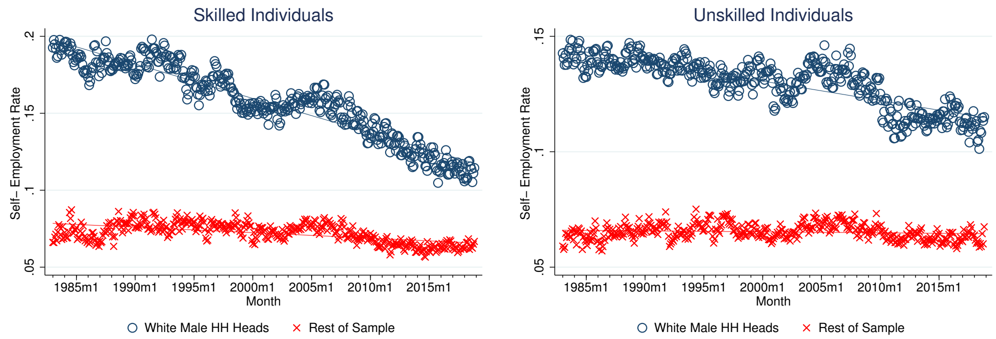
Table 2.6 shows the summary characteristics of the sample's characteristics for employees, self-employed, entering and exiting self-employed. The demographic composition and sample size in this work differs significantly from the PSID sample used in Salgado (2018); with a much larger sample and much high share of non-white and female individuals included. This distinction is not without consequence. As shown in figure 2.11, the overall share and entry into self-employed for white, male, heads of households - the primary component in the author's sample - exhibits much steeper declines(increase) in overall and entry (exit) into self-employment relative to the rest of the sample.

Table 2.6: Summary Characteristics of Sample

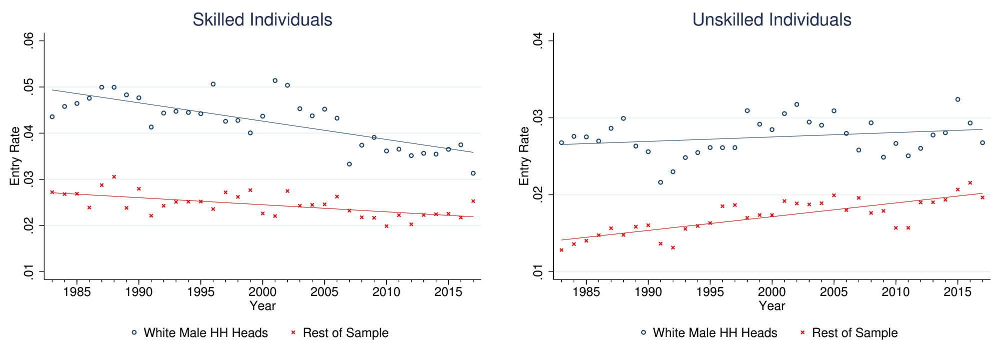
| | Employees | Self-Employed | Entrants | Exiters |
|---|---|---|---|---|
| Age | 42.5 | 45.1 | 42.4 | 43.4 |
| White | 0.820 | 0.886 | 0.839 | 0.839 |
| Male | 0.551 | 0.724 | 0.579 | 0.579 |
| HH Head | 0.587 | 0.659 | 0.597 | 0.598 |
| HS | 0.346 | 0.319 | 0.335 | 0.336 |
| College | 0.287 | 0.273 | 0.281 | 0.281 |
| GTC | 0.367 | 0.408 | 0.384 | 0.384 |
| Incorporated | - | 0.395 | 0.432 | 0.548 |
| N (in 1000s) | 15,636 | 1,809 | 104 | 111 |

*Notes:* The table shows the average age, and share of sample by it's demographic characteristics. HS and GTC denote the share of the sample with a high school degree and the the share with greater than a college degree, respectively. The first two columns, employees and self-employed is from the CPS monthly data while the last two columns show data from the matched CPS sample.

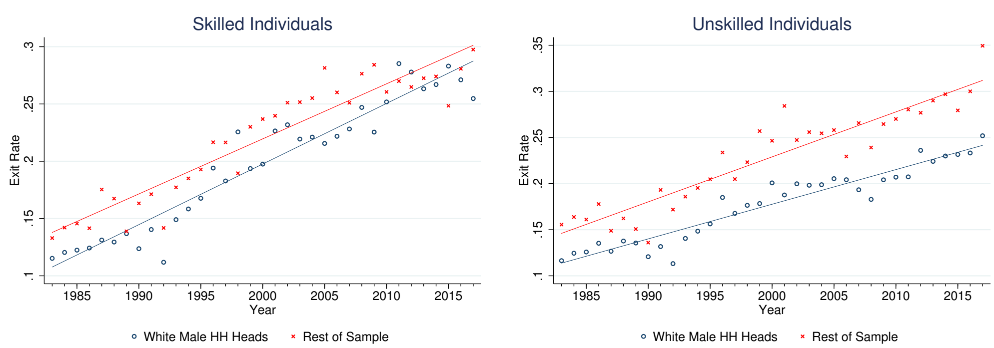
Figure 2.11: Entrepreneurial Dynamics for White Male HH Heads and the rest of sample




(a) Self-Employment Rate




(b) Entry Rate




(c) Exit Rate

Notes: Sample includes full-time, non-agricultural employees aged between 25 and 65 with at least a high school degree from the basic monthly CPS files. The self-employment rate is the share of the sample that is identified as self-employed.

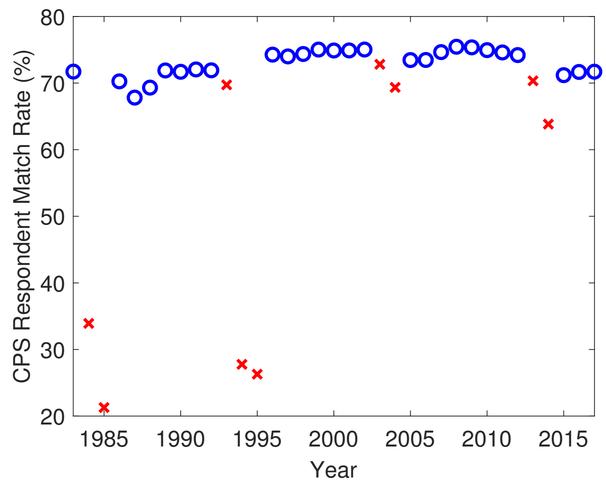
**Adjusting for the CPS Redesign** To measure transitions in and out of self-employment it is important to have consistent variable definitions across sample periods.

To account for the two major redesigns of the CPS that took place in 1994 and 2004[20] we make adjustments for our measures of selection into and out of entrepreneurship. There is a scant literature on adjusting for the CPS redesigns with a notable exception being Polivka and Miller (1998)who provide multiplicative adjustment factors for various aggregate measures derived to adjust for the 1994 redesign. These adjustment factors cannot be applied to our work as they do not include the subgroups relevant to this paper. Additionally as we control for a variety of controls in estimating the entry and exit rates we necessarily require detailed micro-data and cannot rely on aggregate adjustment factors alone.

Instead, as in Polivka and Miller (1998), we exploit the slow phase-in of redesigns in the CPS to justify the assumptions that underlie our adjustment method. In particular, since changes in the CPS are incorporated slowly over a number of months it is still possible to match respondents across months during the redesign transition period. However, since a subset of a given sample will be surveyed with the new questionnaire in the following period, the respondent match rate is lower during the phase-in periods. Naturally the number of respondents is also lower during these periods. Figure 2.12 shows the percent of the sample that is matched across months in the CPS monthly files pooled by year. The 1994 redesign results in lower match rates in 1993, 94 and 95 while the 2004 redesign results in lower match rates in 2003 and 2004.

[20]See Polivka and Miller (1998) and Shoemaker (2004) for details on the 1994 and 2004 redesigns respectively. Adjustments for the 2013/14 redesign is not possible using our method as we do not observe a sufficient number of samples following the redesign.

Figure 2.12: Match Rate




To make our adjustment we assume that the entry and exit rates experience only a temporary *level* shift during those years affected by the redesign. As a justification of this consider five years of raw survey data labeled $\{s_1, s_2, x, t_4, t_5\}$ where $s_i$ and $t_j$ represent redesigned surveys conducted in year $i$ and $j$ and $x$ represents the transition year which, similar to the CPS, includes a mix of type $s$ and $t$ respondents. Label the resulting matched sample as$\{s_{12}, s_2x, xt_4, t_{45}\}$. The data sets$s_2x$ and $xt_4$ are potentially impacted by the redesign and$s_{12}$and $t_{45}$are not. While the $s$ and $t$ type questionnaires are different as long as the variable definitions and methods of measurement are consistent across the two survey types the transition rates from the matched samples $s_{12}$and $t_{45}$will be comparable over time[21]. Although the 1994, and to a lesser extent the 2004, redesigns were significant they do not alter the definitions and measurements of the variables of interest in this paper. For instance, the 1994 redesign introduced additional educational attainment categories yet both the pre

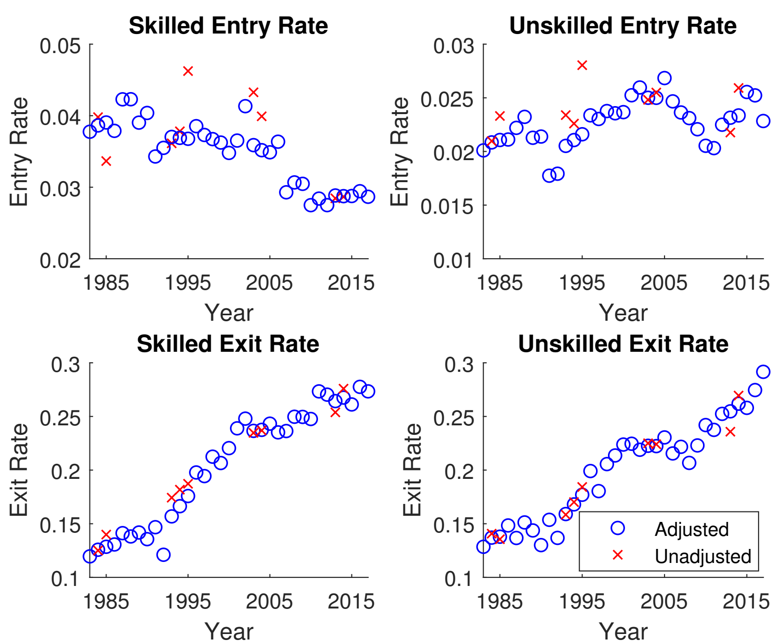
[21] As an example, consider the CPS prior to 1983. During this time it was only possible to identify the unincorporated self-employed while after 1983 it became possible to identify both the incorporated and unincorporated self-employed. This constitutes a permanent and significant change in the definition of who is self-employed. So when we compare, say, the entry rate into self-employment prior to and following the redesign we will observe a permanent level shift following the redesign.

and post redesign education variables allow us to identify skilled and unskilled individuals as defined above in a consistent manner. Given this we take as given that the entry and exit rates prior to and following the redesign are comparable and do not need to be adjusted to be comparable across time.

All that remains is to address the potentially incomparable transition year data; $s_2x$ and $xt_3$. Since we only match $t$ type respondents in $xt_3$ and $s$ type respondents in $s_2x$ it is possible that measures derived from these data are comparable across time. However, for this to be true it must be the case that that phase-in samples are designed so that all subgroups of interest, say self-employed with at least a college degree, are randomly assigned to $s$ and $t$ type questionnaires. As outlined in footnote 4 in Polivka and Miller (1998) this is not how the redesign took place. Instead following an initial introduction of the new survey to subgroup of respondents the older survey was completely phased out over consecutive months . As we pool monthly data at the annual level it is a certainty that subgroups of interest will not randomly assigned across $s$ and $t$ type questionnaires during the transition period. As such, measures derived from the matched data $s_2x$ and $xt_3$ may have unpredictable level shifts from the "true" measure of entry rate. Notice that these level difference are not due to a changes in variable definitions but due to differences in sample sizes as represented in the match rate.

To adjust for these level shifts we perform a probit regression on, say the entry rate$e_{i,t}$, including all relevant controls as described in the main text and in addition include dummies for those years impacted by the redesign. We also include dummies for those year immediately prior to and after the implementation of the redesign. For the 1994 redesign we include dummies for 1992,93,94, 95 and 96 and for the 2004 redesign we include dummies for 2002, 03 and 04. The marginal effect of these dummies are then subtracted from the unadjusted expected predicted entry rate derived from a probit regression without the redesign dummies. This impacts the expected predicted entry rate only those years that are effected by the redesign. Figure 2.13 plots the unadjusted and adjusted entry rate and exit rate from the matched monthly CPS data. Notice this data is not smoothed as in panels b) and c) of figure 2.1. The discrepancies between the adjusted and unadjusted entry rates is larger than that for exit rates. This is intuitive as the entry rates captures a smaller subgroup, transitions into self employment, across surveys and this population is less likely to be evenly distributed across surveys during the phase-in period. Additionally, the more comprehensive redesign in 1994 requires a larger adjustment than the 2004 redesign. The figure also highlights the lack of a permanent level shift following either the 1994 or 2004 redesigns.

Figure 2.13: Adjusted and Unadjusted Entry and Exit Rates in the Matched March CPS




**Measuring Skill Bias in Change of Self-Employment, Entry and Exit Rates** We first begin constructing the self-employment, entry and exit rate for both skill types at the state level for the pooled years 1983-1995 and 1996-2007. Second, we compute the percentage change, by skill type, in each of the three rates between the two year bins. The difference in this percentage change between skilled and unskilled individuals is reported on the vertical axis of figure 2.4. For instance, if the entry rate for unskilled and skilled individuals declined by 5 and 20 percent respectively in a given state then the skill bias in the decline in entry rate would be the differences between these two percentages, that is, -15% or -0.15.

### March Supplement

The March Annual Social and Economic Conditions (ASEC) supplement to the CPS includes information on income and is used to measure the skill premium and as well and entry and exit rates. Before outlining these measure we should note that it is possible to identify "hybrid" entrepreneurs, that is those individuals that are concurrently employed by others and self-employed in the CPS March files. We identify and sort these respondents in using the IPUMS variables incwage and incbus which report a respondent's annual wage and business income, respectively. Those individuals that earn non-zero amounts of both types of income are identified and then sorted as either an employee or self-employed based on the occupation in which they earn a higher amount. Importantly, we only include those workers that report at least 5,000 2010USD in wage income and those entrepreneurs that report non-zero incomes. Additionally we exclude those that work fewer than 20 hours in their specified occupation. All other sample restrictions are identical to those used with the month data.

**Estimating Skill premium** We follow Acemoglu (2002) in constructing worker's skill premium. The relevant measure of worker's income is constructed from the IPUMS variables incwage and is the annual income reported in real 2010 USD. Those with no earnings and the remaining lowest 1 percent of earners are dropped from the sample. Top-coded incomes are assumed to be 1.5 times the top-code. The reported measure of skill premium is the coefficient on a dummy variable for those with at least a bachelor's degree in an OLS regression of log income with a variety of controls. The controls are; (1) a quartic in years of potential experience, (2) gender dummy , (3) race (white/non-white) dummy, (4) interactions between race and gender dummies (5) state dummies (6) additional dummies for educational categories. The state level skill premium is computed analogously with the exception that we do not include state dummies. Years of potential experience $E = age - S - 6$ is defined by assuming that an individual's schooling starts after age six and years of schooling, $S$, are assumed using the IPUMS variable educ. This variable reports the highest level of educational attainment of a respondent and the correspondence between years of schooling and this variable is detailed in table 2.7.

Table 2.7: Years of Schooling in March CPS, 1965-2014

| educ | Years ($S$) | Share (%) | educ | Years ($S$) | Share (%) |
|---|---|---|---|---|---|
| None or preschool | 0 | 0.3 | 12th grade, diploma unclear | 12 | 16.0 |
| Grades 1, 2, 3, or 4 | 2.5 | 0.3 | High school diploma or equivalent | 12 | 17.8 |
| Grade 1 | 1 | 0.1 | 1 year of college | 13 | 2.6 |
| Grade 2 | 2 | 0.1 | Some college but no degree | 13.5 | 10.0 |
| Grade 3 | 3 | 0.2 | 2 years of college | 14 | 3.4 |
| Grade 4 | 4 | 0.3 | Associate's degree, occupational/vocational | 14 | 2.9 |
| Grades 5 or 6 | 5.5 | 0.8 | Associate's degree, academic program | 14 | 2.8 |
| Grade 5 | 5 | 0.3 | 3 years of college | 15 | 1.2 |
| Grade 6 | 6 | 0.7 | 4 years of college | 16 | 5.4 |
| Grades 7 or 8 | 7.5 | 0.7 | Bachelor's degree | 16 | 12.1 |
| Grade 7 | 7 | 0.7 | 5 years of college | 17 | 1.2 |
| Grade 8 | 8 | 2.3 | 6+ years of college | 18 | 2.8 |
| Grade 9 | 9 | 2.3 | Master's degree | 18 | 4.6 |
| Grade 10 | 10 | 3.0 | Professional school degree | 18 | 1.0 |
| Grade 11 | 11 | 2.7 | Doctorate degree | 21.5 | 0.9 |
| 12th grade, no diploma | 12 | 0.6 | | | |

The skill premium for the self-employed is constructed analogously. An important distinction is that the relevant measure of income is the IPUMS variable incbus and those that report zero and negative income are not dropped and instead the log income of these individuals is assumed to be equal to 0. The lowest 1% of earners are trimmed and top-coded incomes are assumed to be 1.5 times the top-code.

**Matching Respondents** We use a similar method to match CPS March respondents as in the basic monthly files. However, since only the March surveys are of relevance individuals appear only once in the sample and are matched from their $n^{th}$ interview to their $(n+4)^{th}$ interview where $n \in \{1, 2, 3, 4\}$. Unlike the monthly files it is not possible to match individuals during those years that the CPS was being redesigned. This includes more minor redesigns such as those during 1983 and 1989. Due to this and to make the comparison with the SIPP data clear we only analyze data after 1996. This is the first year for which matching is possible following the extensive 1994 redesign. The years 2004 and 2014 are excluded from the sample. The resulting matched sample includes in 382,700 interviews or 191,350 unique individuals. Naturally, the matched March CPS sample is much smaller than the analogous matched monthly sample and also features a lower average match rate of around 52%.

**Estimating Entry and Exit Rates** The method used to estimate entry and exit rates from the matched March data is identical to that used with the monthly data.

### 2.8.2 ACS/Census Data

We use data from the American Community Surveys from 2000 to 2017 and data from the 1990 Census to rank occupations by the average wages. We being by creating a consistent set of occupations following the method outlined in David and Dorn (2013). We then use the ACS/Census provided weights to construct measures of labor supply and real hourly earnings. Labor supply is computed using the ACS/Census provided weights and is the annual hours worked which is given by the product of usual weeks and hours worked in a year. Real hourly earnings is ratio of annual earnings and the annual hours worked. The supply of self employed when using the ACS is constructed analogously and entrepreneurs are grouped using their stated occupation as an entrepreneur. Figure 2.5 plots changes in the share of self-employment against the average earnings of occupations which are grouped into percentiles. More concretely, if the share of self-employed in occupation $o$ at time $t$ is $e_{o,t}$ the figure plots:

$$100 \times (e_{o,t+1} - e_{o,t})$$

Wage changes are computed analogously.

Figure 2.6 plots the percentage changes in share of new entrepreneurs based on an individuals prior occupation in employment i.e. $o'$. What we are interested in is the share of employees in each occupation that become entrepreneurs. So, if for an occupation $o'$ there are a total of $L_{o'}$ employees and $E_{o'}$of them become entrepreneurs in a given period, we are interested in $\frac{E_{o'}}{L_{o'}}$ and changes in this ratio over time. Instead, what we measure is the share of new entrepreneurs, from a given occupation, among all new entrepreneurs; $\frac{E_{o'}}{\Sigma_{o'} E_{o'}}$in the CPS data. Then we divide this with the share of employees in a given occupation among all employees:$\frac{L_{o'}}{\Sigma_{o'} L_{o'}}$. We then report log differences in this ratio, that is:

$$100 \times \left( \log \left( \frac{E_{o',t+1}}{L_{o',t+1}} \right) - \log \left( \frac{E_{o',t}}{L_{o',t}} \right) + \Omega \right)$$

where $\Omega$ is the change change in entry rate between the two periods $\left( \log \left( \frac{\Sigma_{o'} E_{o',t}}{\Sigma_{o'} L_{o',t}} \right) - \log \left( \frac{\Sigma_{o'} E_{o',t+1}}{\Sigma_{o'} L_{o',t+1}} \right) \right)$. Notice that $\Omega$ is a level shifter and does not impact the relationship between changes in entry rate and the skill percentile.

When using the matched CPS data to track changes in the transitions into self-employment, we combine the share of new entrepreneurs

### 2.8.3 SIPP Data

The Survey of Income and Program Participation (SIPP) is used to complement the findings from the CPS monthly and March data. The SIPP has the advantage of being a longitudinal survey which features detailed information on incomes and hours worked. Similar to the March CPS data we are able to identify those individuals that are earning income as both an employee and self-employed. In addition, to using data on income we also use data on hours worked in each occupation to classify an individual as an employee or wage worker. Namely we assign an individual to be in that occupation in which they earn the most and work more hours. Data from all waves of the 1996, 2001, 2004 and 2008 SIPP panels are utilized. The final pooled sample consists of 232,541 unique individuals that amount to 7.1 million monthly observations. This averages to around 31 months of appearances in the final sample per individual. All sample restrictions are identical to those used with the CPS monthly data.

**Estimating Entry and Exit Rates** The method used to estimate entry and exit rates from the SIPP is identical to that used with the monthly and March data.

## 2.9 Model Appendix (Not intended for publication)

The entrepreneur solves the following problem:

$$\pi(z) = \max_{\{L_s, L_u\}} Y(z) - w_s L_s - w_u L_u$$

First order conditions with respect to $L_s$ and $L_u$ are:

$$z\mathrm{A}\eta \left[\Theta_s L_s^{\sigma} + L_u^{\sigma}\right]^{\frac{\eta}{\sigma}-1} \Theta_s L_s^{\sigma} = w_s L_s$$

$$zA\eta \left[\Theta_s L_s^{\sigma} + L_u^{\sigma}\right]^{\frac{\eta}{\sigma}-1} L_u^{\sigma} = w_u L_u$$

Combining these two equations gives the wage ratio between the high skilled and the low skilled:

$$\frac{w_s}{w_u} = \frac{\Theta_s L_s^{\sigma-1}}{L_u^{\sigma-1}}$$

This implies:

$$L_u = \left(\frac{w_s}{w_u \Theta_s}\right)^{\frac{1}{1-\sigma}} L_s$$

$$\Rightarrow \Theta_s L_s^\sigma + L_u^\sigma = L_s^\sigma \left[\Theta_s + \left(\frac{w_s}{w_u \Theta_s}\right)^{\frac{\sigma}{1-\sigma}}\right]$$

Substitute the above equation into the FOC conditions:

$$w_s = zA\eta\Theta_s L_s^{\eta-1} \left[\Theta_s + \left(\frac{w_s}{w_u \Theta_s}\right)^{\frac{\sigma}{1-\sigma}}\right]^{\frac{\eta}{\sigma}-1}$$

Hence we can express labor demand of high skilled and low skilled workers in the following way:

$$L_s = z^{\frac{1}{1-\eta}} A^{\frac{1}{1-\eta}} \{\eta \frac{\Theta_s}{w_s} \left[\Theta_s + \left(\frac{w_s}{w_u \Theta_s}\right)^{\frac{\sigma}{1-\sigma}}\right]^{\frac{\eta}{\sigma}-1} \}^{\frac{1}{1-\eta}}$$

and

$$L_u = \left(\frac{w_s}{w_u \Theta_s}\right)^{\frac{1}{1-\sigma}} \{zA\eta \frac{\Theta_s}{w_s} \left[\Theta_s + \left(\frac{w_s}{w_u \Theta_s}\right)^{\frac{\sigma}{1-\sigma}}\right]^{\frac{\eta}{\sigma}-1} \}^{\frac{1}{1-\eta}}$$

Then the two labor market clearing conditions are:

$$\lambda F_s(\bar{z_s}) = \int_{\bar{z_s}}^{\infty} \lambda L_s(z, w_u, w_s)\ dF_s(z) + \int_{\bar{z_u}}^{\infty} (1-\lambda) L_s(z, w_u, w_s)\ dF_u(z)$$

$$(1-\lambda) F_u(\bar{z_u}) = \int_{\bar{z_s}}^{\infty} \lambda L_u(z, w_u, w_s)\ dF_s(z) + \int_{\bar{z_u}}^{\infty} (1-\lambda) L_u(z, w_u, w_s)\ dF_u(z)$$

We also have two boundary conditions that equate the payoff to being a worker and entrepreneur at the margin. In particular, we require that:

$$\pi(\bar{z_s}) = w_s \text{ and } \pi(\bar{z_u}) = w_u$$

From the equations above we know what the profit of being an entrepreneur $\pi(z)$ is:

$$\pi(z) = zA(1-\eta)[\Theta_s L_s^\sigma + L_u^\sigma]^{\frac{\eta}{\sigma}}$$

$$\pi(z) = (zA)^{\dfrac{1}{1-\eta}} (1-\eta) \left[\Theta_s + \left(\frac{w_s}{w_u \Theta_s}\right)^{\frac{\sigma}{1-\sigma}}\right]^{\dfrac{\eta(1-\sigma)}{(1-\eta)\sigma}} \left(\eta \frac{\Theta_s}{w_s}\right)^{\dfrac{\eta}{1-\eta}}$$

Then the boundary conditions yield:

$$g_1(w_u, w_s, r) \equiv z_s = \frac{1}{A}(1-\eta)^{-(1-\eta)} (\eta\Theta_s)^{-\eta} w_s \left[\Theta_s + \left(\frac{w_s}{w_u \Theta_s}\right)^{\frac{\sigma}{1-\sigma}}\right]^{-\frac{\eta(1-\sigma)}{\sigma}}$$

$$g_2(w_u, w_s, r) \equiv z_u = \frac{1}{A}(1-\eta)^{-(1-\eta)} (\eta\Theta_s)^{-\eta} w_u \left[\Theta_s + \left(\frac{w_s}{w_u \Theta_s}\right)^{\frac{\sigma}{1-\sigma}}\right]^{-\frac{\eta(1-\sigma)}{\sigma}}$$

Using the Pareto Distribution allows us to get the further explicit forms of the two labor market conditions.

$$\lambda - \frac{\lambda}{g_1(w_u, w_s)^{\xi_s}} = \int_{g_1(w_u,w_s)}^{\infty} \lambda L_s(z, w_u, w_s) \frac{\xi_s}{z^{\xi_s+1}} \, dz + \int_{g_2(w_u,w_s)}^{\infty} (1-\lambda) L_s(z, w_u, w_s) \frac{\xi_u}{z^{\xi_u+1}} \, dz$$

$$1-\lambda - \frac{1-\lambda}{g_2(w_u, w_s)^{\xi_u}} = \int_{g_1(w_u,w_s)}^{\infty} \lambda L_u(z, w_u, w_s) \frac{\xi_s}{z^{\xi_s+1}} \, dz + \int_{g_2(w_u,w_s)}^{\infty} (1-\lambda) L_u(z, w_u, w_s) \frac{\xi_u}{z^{\xi_u+1}} \, dz$$

Denote some constants to simplify notations:

$\alpha_s = \frac{1-\xi_s+\xi_s\eta}{1-\eta}$ ,

$\alpha_u = \frac{1-\xi_u+\xi_u\eta}{1-\eta}$.

$\bar{L}_s = \{\eta A \frac{\Theta_s}{w_s}\left[\Theta_s + \left(\frac{w_s}{w_u\Theta_s}\right)^{\frac{\sigma}{1-\sigma}}\right]^{\frac{\eta}{\sigma}-1}\}^{\frac{1}{1-\eta}}$ ,

$\bar{L}_u = \left(\frac{w_s}{w_u\Theta_s}\right)^{\frac{1}{1-\sigma}}\{\eta A \frac{\Theta_s}{w_s}\left[\Theta_s + \left(\frac{w_s}{w_u\Theta_s}\right)\right]^{\frac{\eta}{\sigma}-1}\}^{\frac{1}{1-\eta}}$.

Then we have

$$\lambda - \frac{\lambda}{\bar{z_s}^{\xi_s}} = \bar{L}_s[\frac{\lambda\xi_s(z_{\max s}^{\alpha_s} - \bar{z_s}^{\alpha_s})}{\alpha_s} + \frac{(1-\lambda)\xi_u(z_{\max u}^{\alpha_u} - \bar{z}^{\alpha_u})}{\alpha_u}]$$

$$(1-\lambda) - \frac{1-\lambda}{\bar{z}_u^{\xi_u}} = \bar{L}_u[\frac{\lambda\xi_s(z_{\max s}^{\alpha_s} - \bar{z_s}^{\alpha_s})}{\alpha_s} + \frac{(1-\lambda)\xi_u(z_{\max u}^{\alpha_u} - \bar{z}^{\alpha_u})}{\alpha_u}]$$

where we set the maximum value of the entrepreneurial skill for both groups to be positive infinity.

# Chapter 3

# The Timing of Childbearing: Theory and Quantitative Analysis

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## 3.1 Introduction

Demographic transition has been one of the central issues in the broad field of development economics. This is not only because of academic curiosity for understanding the causes of such a significant socioeconomic change, but also because of its strong implications for the speed of economic development and the misery of poverty traps. To study demographic transition, however, one must recognize that fertility choice includes three distinct decisions: the number of children, the quality of children, and the timing and spacing of births. A vast literature has been devoted to studying the first two of these aspects of fertility by documenting the decline in the total fertility rate over the past century and the associated

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rise in the quality of children. Much less discussed is the timing of fertility, which has undergone changes of the same order of magnitude as those observed in the quantity and quality dimensions. The focus of the literature on the quantity-quality trade-off is not surprising, because the quantity and quality aspects of children can be handled by standard demand and supply analysis without the need for a full dynamic model. By contrast, studying childbearing age requires a fully specified dynamic process of demographic and labor decisions over a female's entire life, which complicates the analysis greatly. In the present paper, we endeavor to examine this much less-explored dimension of fertility choice, hoping to better understand the determinants of timing and spacing of births. As such, our findings would help generate useful implications for the interplays between demographic transition and economic development.

Over the past five decades, the rise in the childless rate and the age at first birth has been commonly observed in many developed countries in Western Europe and North America as well as in fast growing countries in Asia. Such a positive trend is not only quantitatively large, but robust across regions and ethnic groups (given some noticeable disparities). For example, by the year 1990, almost half (49%) of Swedish women in the 25-29 age group were still childless. The comparable figures for the U.S., Germany and the Netherlands were 42%, 57% and 61%, respectively. Let us take a closer look at the U.S. using the Current Population Survey (CPS) data. The average and median age of first birth increased by 1.405 (2) years, from 24.584 (24) for 1940-1945 cohort to 25.989 (26) for 1950-1955 cohort. If we look at different skill groups, the age at first birth was 24.506 and 25.596 for the low-skilled group and the high-skilled group respectively, and the number of years of first spacing for the two skill groups were 2.518 and 3.249. It's clear to see that the decision on childbearing timing varies across time and between skill groups. Despite the empirical significance and important implications, a systematic analysis of the joint decisions of birth timing and other fertility and individual choices remains relatively under-investigated.

In an attempt to analyze the timing of births, we develop a continuous-time lifecycle model, extending the Ben-Porath framework along the lines proposed by Mullin and Wang (2008) by incorporating birth timing as a decision variable and allowing for heterogeneity of human capital. To maintain tractability, we abstract from out-of-wedlock childbearing and multiple births.[5] Once a woman is married, she decides the timing of the birth, the allocation of time to work, and human capital accumulation. The model is solved in two steps. In the first stage, given a birth timing, we pin down all endogenous variables other than the birth timing. The endogenous timing of childbearing, modeled as a continuous variable, is then determined in the second stage. Other than the conventional wisdom that views better schooling (higher human capital and hence higher opportunity cost of having children) and child preference as the two main drivers determining the timing of childbirth, we embed three new channels in the model: (1) the leisure loss channel – a married woman will suffer a leisure loss for a certain period if she decides to have a child; (2) the "child penalty" channel – a woman will have a productivity loss and human capital depreciation when having a child; and (3) the income security (husband income) channel. We examine all the above channels, both theoretically and quantitatively, and study how they shape the decision on childbearing timing.

Based on this life-cycle framework, we are able to obtain the following theoretical predictions that are useful in guiding the empirical analysis. First, birth timing is delayed if human capital rises as a result of better education or improved work productivity, or if industry-and occupation-specific factors feature greater productivity loss from childbearing. Second, a reduction in income security leads to postponement in births. Third, birth timing is shortened if women have strong preferences for quality-adjusted children or less leisure loss.

[5]Although our findings can be generalized to including such extra features, the model becomes unnecessarily complicated without adding much additional insight.

We use data from CPS to construct two synthetic cohorts: 1940-1945 cohort and 1950-1955 cohort, and we allow for human capital heterogeneity by analyzing two skill groups. We calibrate the model targeting the average moments of the two cohorts. Quantitative analysis show that the duration of fertility-related productivity loss and income security (husband income) play a crucial role in understanding the differences in first spacing and the age at first childbearing between the two skill groups. These two novel channels together can explain 71.3% of the difference in the first spacing decisions between skill groups; each contributes around 35%. In particular, if we shut down the heterogeneity of the duration of fertility-related productivity loss, the gap in the first spacing is 13.13 years; if we assume the income security (husband to wife income ratio) is homogenous, the gap becomes 13.71 years; however if we only shut down the heterogeneity in human capital or productivity, the gap is 6.66 and 5.04 years respectively, the sum of which is less than the effect from productivity loss or income security alone. In addition, the counterfactual experiments show that fertility preference is more important than loss from leisure in terms of explaining different timing of childbearing between skill groups. Moreover, the low-skilled women are more vulnerable to changes in labor productivity, leisure loss, income security, and fertility preference, implying that they will defer their childbearing timing decision to a larger extent compared to high-skilled women.

An outline of the paper follows. Section 3.1.1 discusses related literature. Section 3.2 describes empirical facts. Section 3.3 outlines the life-cycle model. In section 3.4 we calibrate the model and perform counterfactual experiments. Section 3.5 discusses extensions, and section 3.6 concludes.

### 3.1.1 Related Literature

Our paper is related to the broader literature on demographic transition and economic development. Early studies along these lines focused on predicting fertility for the entire population or explaining differences in fertility across sub-populations (see Spengler and Duncan (1956), 1956, Lee (1987), and Becker (1988). This analysis relied heavily on changes in the age, sex, and marital composition of the population, but rarely attempted to formally model the evolution of these inputs. The inability of these models to foresee the sharp fertility decline in the early 1930s and the subsequent rise in the 1950s instigated a call for deeper research in this area (cf. Becker (1960); Easterlin et al. (1968)). Since this broader literature is not as relevant, we will only highlight a few such studies.[6] In particular, fertility became an endogenous variable in more recent dynamic models. Barro and Becker (1989) and Becker et al. (1990) are among the first to emphasize the interaction of the family with other macro variables related to economic development. Not only does a household's childbearing decision depend on economic conditions, but these decisions also feed back into the economy, influencing labor and capital accumulation decisions. Such interactions have been found to be empirically significant by Wang et al. (1994) using U.S. data. A common feature of the endogenous growth and fertility literature is its focus on the quantity-quality tradeoff in fertility decisions, leaving the decision on the timing of birth largely unexplored.

To our knowledge, there are only a handful of theoretical studies on birth timing. In their pioneering studies, Happel et al. (1984) and Cigno and Ermisch (1989) illustrate the sharp increase in the timing of first birth in the western world and provide basic microeconomic analysis along the lines of Becker.[7] Not until a decade ago have there been studies using dynamic general equilibrium approaches. In this still thin literature, Conesa (2002), Iyigun (2000) and Caucutt et al. (2002) construct discrete-time models whereas Mullin and Wang (2002) develop a continuous-time framework. Conesa (2002) introduces idiosyncratic uncertainty in future labor earnings and analyzes its impact on fertility decisions by regarding children as irreversible consumption durables. In the model, the evolution of human capital

[6] Hotz et al. (1997) provides a comprehensive overview of this literature.

[7] See also Yamaguchi and Ferguson (1995) from the sociological aspect.

is treated as exogenous. Caucutt et al. (2002) include marriage and the quantity and quality dimensions of children as endogenous variables. To keep their model tractable, life is divided into five periods in which in the latter three one is an adult, but only fertile for the first two of those three intervals. Thus, the timing of birth is reduced to a binary choice. In addition, the human capital of adults evolves based on time spent in the labor market (i.e., a learning-by-doing rather than an education setup), which eliminates any tradeoff between human capital accumulation and market production. In contrast to these two papers, endogenous human capital accumulation is the key element in Iyigun (2000) and Mullin and Wang (2002). Iyigun (2000) considers a three-period overlapping-generation economy with the birth timing also modeled as a binary choice. Yet, human capital is accumulated via education and hence there is an immediate trade-off between childbearing and human capital accumulation. Mullin and Wang (2002) also model human capital accumulation to depend on education. They permit women to differ in their initial stock of human capital and examine birth timing over the distribution of heterogeneous women by calibrating to the U.S. economy. Our theoretical model complements the literature by considering occupation-specific and income security factors, as well as preference and mother's age factors, in addition to standard employment, income and education factors.

Equally thin is the empirical literature on birth timing. In their pivotal studies, Heckman and Walker (1990b) and Heckman and Walker (1990a) find that while female wages delay child birth timing in Sweden to all conceptions, husband incomes shorten it when marital status is excluded. An interesting result is that the postponement effect of female wages is the strongest through women's first births. Using Dutch data, Bloemen and Kalwij (2001) establish that more educated women, by changing their employment status, lengthen their timing of child birth. In addition to education, Merrigan and Pierre (1998) also identify significant religious and regional effects on birth timing and spacing in Canada. More recently, Gutiérrez-Domènech (2008) applies Spainish data and estimates a positive effect of female employment on birth timing. Using data from developing countries, Bhalotra and Van Soest (2008) document that the death of a child in India significantly reduces spacing for the next birth, whereas Tsay and Chu (2005) identify that both years of schooling and son preferences are important for birth timing in Taiwan.

One of the main obstacles in the empirical literature is to what extent the existing evidence between a mother's fertility decision and her decision of human capital can be interpreted as casual. Different from the previous studies focusing on the impact of a woman's career on her fertility decision, Miller (2009) attempts to identify the casual effect in another direction—the impact of delayed motherhood on a woman's career. Using the biological shocks as instruments, she found out that motherhood delay increases the wages rate by 3%, and career hours worked by 5%. Likewise, Bailey et al. (2012) study the diffusion of contraception pills and found out the pill (and the fertility reduction) can account for 30% of the convergence of the gender wage gap by 1990s.[8] In spite of the recent developments, there is still no clear evidence about the casual effect of a woman's career on her timing and spacing of birth choice.

Although the timing of births has not received much attention in the growth and development literature, the increase in the rate of unwed mothers over the last thirty years and this population's heavy dependence on government assistance has led to a vast literature on this topic and related issues amongst labor economists. The bulk of this research focuses on the effect of government transfer programs and marital prospects on the fraction of women having teenage births and the marital status of those women at the time of birth (see Hoyne (1997) and Moffitt (1995)). More recently, this line of the literature has increased both the choices available to women and the complexity of their utility functions (see Neal

[8] Goldin and Katz (2002) is the first one that explores the relation between the diffusion of contraception pill and a woman's marriage and career choice. They found out that the birth control pill delays a woman's age of first marriage, increases year of schooling, and raises working wages and hours.

(2001) and Nechyba (2001)), but these models continue to share two common traits: (i) fertility decisions are limited to a small number of discrete decisions (e.g., teen versus adult or legitimate versus illegitimate births); and (ii) women optimize in a static environment in which there are no dynamic interactions. In contrast to this literature, our work concentrates on the effects of economic conditions on the commencement of childbearing for all women, not just those at risk of teenage or illegitimate childbearing, and accounts for the dynamic interactions between fertility decisions and other economic factors.

## 3.2 Data

We are interested in the two cohorts of females in the United States: 1940-1945 cohort and 1950-1955 cohort, before and after the baby boom respectively. Since the focus of this paper is on childbearing timing, we restrict the sample to females over 35 years old as such age range is close to the end of fecundity cycle. Due to the sample size limitation of CPS, we perform synthetic cohort analysis, in particular, we use the samples of females age 35-40 years old in survey year 1980 , those age 36-41 years old in 1981, those age 37-42 years old in 1982, and those age 38-42 years old in 1983 to construct the first cohort, and for the second cohort, we use the samples of females age 35-40 years old in survey year 1990, those age 36-41 years old in 1992, and those age 38-43 years old in 1995. We drop the samples who got married before graduation and who had the first child before marriage since the model starts from the age that a women is married and this paper is abstracting from the out-of-wedlock childbearing. Since we are also interested in studying the differences in childrearing timing decisions for females with different education level, we define two skill groups by using the measure of years of schooling. We use “high school" as the threshold to differentiate two skill groups, in particular, the low-skilled females are those who were high-school graduates, and high-skilled females are those who had some college experience or above. We dropped the high-school dropouts from the sample.

Table 3.1 provides the summary statistics of these two cohorts. It can ben seen that the average age at first birth increased by 1.405 years and the median age at first birth increased by 2 years. Similarly, the average first spacing rose by 1.068 years and the median rose by 1 year. The average fertility rate drop by 0.243.

Table 3.2 provides further details for two skill groups. On average, high-skilled females tended to get married and start childrearing activities at a later age compared to low-skilled females, and the first spacing was also bigger for high-skilled females; nevertheless, low-skilled females had a higher average number of children. Another interesting finding is that compared to the low-skill group, the high-skill group deterred their marriage and childrearing decisions more if we look at the difference across two cohorts.

Table 3.1: Summary Statistics

| | 1940-1945 cohort | | 1950-1955 cohort | | Difference | |
|---|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Mean | Median |
| Age at first marriage | 22.044 | 22.000 | 22.411 | 22.000 | 0.368 | 0 |
| Age at first birth | 24.520 | 24.000 | 25.955 | 26.000 | 1.434 | 2.000 |
| First spacing | 2.477 | 2.000 | 3.543 | 3.000 | 1.066 | 1.000 |
| Fertility | 2.403 | 2.000 | 2.160 | 2.000 | -0.243 | 0 |
| Years of Schooling | 14.129 | 14.000 | 14.363 | 14.000 | 0.234 | 0 |
| Number of Observations | 8623 | | 6774 | | | |

Table 3.2: Summary Statistics by Skill Groups (Mean)

| | 1940-1945 cohort | | 1950-1955 cohort | | Difference | |
|---|---|---|---|---|---|---|
| | Low Skill | High Skill | Low Skill | High Skill | Low Skill | High Skill |
| Age at first marriage | 21.945 | 22.104 | 22.043 | 22.579 | 0.098 | 0.475 |
| Age at first birth | 24.100 | 24.780 | 25.031 | 26.374 | 0.931 | 1.595 |
| First spacing | 2.155 | 2.675 | 2.987 | 3.796 | 0.832 | 1.120 |
| Fertility | 2.437 | 2.381 | 2.162 | 2.159 | -0.275 | -0.222 |
| Years of Schooling | 12.000 | 15.443 | 12.000 | 15.437 | 0.000 | -0.006 |
| Human capital | 3.360 | 3.360 | 4.270 | 4.277 | 0.910 | 0.917 |

Table 3.3: Summary Statistics by Skill Groups (Median)

| | 1940-1945 cohort | | 1950-1955 cohort | | Difference | |
|---|---|---|---|---|---|---|
| | Low Skill | High Skill | Low Skill | High Skill | Low Skill | High Skill |
| Age at first marriage | 21.000 | 22.000 | 21.000 | 22.000 | 0.000 | 0.000 |
| Age at first birth | 23.000 | 24.000 | 25.000 | 26.000 | 2.000 | 2.000 |
| First spacing | 1.000 | 2.000 | 2.000 | 3.000 | 1.000 | 1.000 |
| Fertility | 2.000 | 2.000 | 2.000 | 2.000 | 0.000 | 0.000 |
| Years of Schooling | 12.000 | 16.000 | 12.000 | 16.000 | 0.000 | 0.000 |
| Human capital | 3.360 | 3.360 | 4.411 | 4.411 | 1.050 | 1.050 |

## 3.3 The Theoretical Framework

In this section, we extend the lifecycle model of Ben-Porath by introducing birth timing as a one of the key decision variables facing each fertile woman who has perfect foresight. We assume throughout that there is no out-of-wedlock childbearing and that the only fertility timing decision is *the age at first birth*. As such, we can restrict our attention to timing-quality trade-off by normalizing the population of each cohort of women to one (i.e., one child per woman).

### 3.3.1 The Basic Setup

Time is continuous, indexed by $t$. Each cohort of women is indexed by the age at which they can begin childbearing ($M$), which is the age at marriage under our simplifying assumption. All women will live for $T = M + F$ years, where $F$ measures the length of family life. Her age at first birth is denoted by $M + B$. In addition to the incorporation of human capital that measures the quality dimension of fertility decisions and the associated returns, we consider three important features influencing a woman's optimzing behavior: (i) preference for children inclusive of altruism, gender bias and disutility from childrearing, (ii) income security or husband's income ($\phi$), and (iii) productivity loss due to childbearing.

Denote by $n$ an indicator function for the presence of a child. We assume that, once born, a child yields utility of $U_0$ throughout the remaining of the woman's lifetime but causes a utility loss of $\psi$ and a productivity loss of $\delta$ for a duration of $D$ years of childrearing. Let $I(t \in [M + B, M + F])$ be an indicator function whose value is one upon having a child and $I(t \in [M+B, M+B+D])$ be an indicator function whose value is one over such childrearing years. Without loss of generality, we assume throughout the paper that $B + D < F$, i.e., childrearing only results in a partial loss in productivity over the entire lifetime. We can thus measure the net utility enjoyment of having a child by,

$$NU(B) = U_0 I(t \in [M + B, M + F]) - \psi I(t \in [M + B, M + B + D])$$

For tractability, we further assume that the utility from consuming the composite good $c$ is log-linear and that the mother's lifetime utility $V$ is time-separable with subjective discounting at rate $\rho$. Aside from her childhood valuation that involves no decision-making, the mother's lifetime utility can then be specified as:

$$V = \int_{M}^{M+F} \left[ \frac{c^{1-\sigma}}{1-\sigma} + U_0 I(t \in [M+B, M+F]) - \psi I(t \in [M+B, M+B+D]) \right] e^{-\rho(t-M)} dt \tag{3.1}$$

where $\sigma$ is the inverse of the intertemporal elasticity of substitution.

For simplicity, we are abstracting from retirement decisions, assuming that all women work until the end of the her lifetime. Each woman is endowed with one unit of time throughout, which can be allocated to human capital accumulation ($\eta$) and market activity ($1-\eta$). Since a woman suffers a productivity loss of $\delta$ during her childbearing years of duration $D$, her net time endowment is given by, $[1 - \delta I(t \in [M+B, M+B+D])]$. Each woman with human capital $h$ earns market wages at rate $wh$ (so $w$ can be referred to as the effective wage rate) and makes consumption-saving decision with a risk-free asset $a$ paid at the market interest rate $r$. Assume positive assortative matching with a woman's husband income as a multiple of her own: $\theta wh$, where $\theta > 0$ measures the husband's income factor, or, more generally, the income security factor facing the woman. For simplicity, all husbands are absentees in the sense that we are abstracting from their behavioral considerations in our "kingdom of daughters." Thus, a woman of cohort $M$ accumulates her nonhuman wealth according to:

$$\dot{a} = ra + [1 - \delta I(t \in [M+B, M+B+D])](1-\eta)wh + \theta wh - c \tag{3.2}$$

That is, a woman accumulates asset with net savings, which is the sum of interest income and her own and her husband's wages net of her consumption spending.

In our economy, a woman can accumulate her human capital with her time devoted to education/learning as well as from her peers of cohort $M$ that is in forms of noncompensated human capital spillovers ala Lucas Jr (1988). In contrast to Lucas, such spillovers arise in the accumulation of human capital rather than market good production, and we allow for human capital heterogeneity. In the numerical section, we will have two skill groups for analysis. Denoting the aggregate human capital of cohort $M$ as $H$, we can then specify a woman's human capital accumulation as follows:

$$\dot{h} = \Phi[1 - \delta I(t \in [M + B, M + B + D])]\eta h^{\gamma} H^{1-\gamma} \tag{3.3}$$

where $\Phi > 0$ is the maximum rate of human capital accumulation and $\gamma \in (0, 1)$ with $1 - \gamma$ capturing the strength of the human capital spillover effect.

To close the model, we specify the production of the composite good at time $t$, which is produced with a Ricardian technology,

$$y = AL \tag{3.4}$$

where

$$L = \int_{M}^{M+F} \int_{i \,\in\, \text{cohort}\ \tau} \{[1 - \delta I(t \in [M + B, M + B + D])](1 - \eta)h\}\, did\tau \tag{3.5}$$

which is aggregating over every woman of age $\tau$, over all cohorts currently alive, and over human capital distribution. In a competitive labor market, women are hired at effective wage $w = A$.

### 3.3.2 Intertemporal Optimization

A woman of cohort $t$ (entering the economy at period $t$) solves her intertemporal optimization problem in two steps. In the first and conventional step, she makes optimal consumption-saving decision, human capital investment decision. In the second stage on which our primary focus is, the woman pins down the optimal childbearing time.

The first-stage optimization problem is thus to maximize the lifetime utility specified in (3.1) subject to the two evolution equations (3.2) and (3.3). There are two controls $(c, \eta)$ and two states $(a, h)$. Denote the co-state variables associated with the two evolution equations as $\lambda_a$ and $\lambda_h$, respectively. So the relative price of human capital investment in units of the composite good becomes $p = \lambda_h/\lambda_a$. It is convenience to denote a woman's relative human capital in cohort $t$ as $v = h/H$. The first-order conditions can then be derived as follows:

$$c^{-\sigma} = \lambda_a \tag{3.6}$$

$$\Phi p = wv^{1-\gamma} \tag{3.7}$$

The Euler equations are given by,

$$\dot{\lambda}_a/\lambda_a = \rho - r \tag{3.8}$$

$$\dot{\lambda}_h/\lambda_h = \rho - \Phi v^{\gamma-1} \{[1 - \delta I(t \in [M+B, M+B+D]) (1 - \eta + \gamma\eta) + \theta\} \tag{3.9}$$

While (3.6) is a standard condition governing intertemporal consumption efficiency, (3.7) equates the marginal benefit of human capital investment with its marginal cost measured by foregone wage earnings. Equations (3.8) and (3.9) govern the evolution of the shadow prices of the composite good and the human capital stock.

Totally differentiating (3.6), in conjunction with (3.8), yields the standard Keynes-Ramsey condition governing the dynamic path of consumption:

$$\dot{c}/c = \frac{r - \rho}{\sigma} \tag{3.10}$$

We then follow the dual approach proposed by Bond et al. (1996) to analyze this two-sector growth model by combining the two Euler equations to obtain:

$$\dot{p}/p = \dot{\lambda}_h/\lambda_h - \dot{\lambda}_a/\lambda_a = r - \Phi v^{\gamma-1} \left\{ [1 - \delta I(t \in [M+B, M+B+D])] \,(1 - \eta + \gamma\eta) + \theta \right\} \tag{3.11}$$

This *intertemporal no-arbitrage condition* states that if holding asset yields higher return than accumulating human capital, then to have a nondegerate portfolio it must be that human capital provides a capital gain with $\dot{p}/p > 0$. Importantly, such a gain from accumulating human capital is lower if the woman suffers a productivity loss from childbearing.

### 3.3.3 Childbearing Decision

We are now prepared to solve hypothetical balanced growth equilibrium assuming infinite lifetime with $F \to \infty$ and under a fixed childbearing age $B$. Along a hypothetical balanced growth path, $c$, $a$ and $h$ all grow at constant rates, not necessarily common growth rate, whereas $\eta$, $v$ and $p$ are all constant over time. Our main task is to use this hypothetical balanced growth path to help pin down a woman's birth timing. Only for illustration purpose, the following analysis assumes the common growth rate for $c$, $a$, and $h$.

Under constant returns technologies, it is clear that along such a path, consumption, human capital and non-human asset wealth for each cohort must grow at the same rate $g = \frac{r-\rho}{\sigma}$. Thus, from (3.2) and (3.3), we have:

$$\frac{c}{a} = \frac{\rho + (\sigma - 1)\, r}{\sigma} + [1 - \delta I(t \in [M+B, M+B+D])](1-\eta)A\frac{h}{a} + \theta A \frac{h}{a} \tag{3.12}$$

$$\Phi[1 - \delta I(t \in [M+B, M+B+D])]\eta v^{-(1-\gamma)} = \frac{r-\rho}{\sigma} \tag{3.13}$$

Since $p$ is constant along this hypothetical path, intertemporal no-arbitrage (3.11) implies:

$$\Phi v^{\gamma-1} \left\{ [1 - \delta I(t \in [M+B, M+B+D])] \,(1 - \eta + \gamma\eta) + \theta \right\} = r \tag{3.14}$$

which can be combined with (3.13) to yield:

$$\frac{\eta\left(r-\Phi v^{\gamma-1}\theta\right)}{1-\eta+\gamma\eta}=\frac{r-\rho}{\sigma}$$

Rearrange the above equation:

$$v=\left[\frac{\Phi\theta\sigma\eta}{\sigma\eta r-(r-\rho)\left(1-\eta+\gamma\eta\right)}\right]^{\frac{1}{1-\gamma}} \tag{3.15}$$

That is, $v$ is a function of $\eta$. Other things being equal, stronger human capital spillovers $(1-\gamma)$ imply a more severe free-rider problem, thereby discouraging human capital investment and reducing the relative human capital stock of a woman. For $v$ to be positive, we have to impose the following condition.

**Condition V** $\eta>\frac{r-\rho}{\sigma r+(1-\gamma)(r-\rho)}$.

That is, the endogenous chosen fraction of time devoted to human capital accumulation cannot be too small. The expression (3.15) also states that when other things are held equal, we have

$$\frac{dv}{d\eta}=\frac{-1}{(1-\gamma)\,\eta}\left[\frac{\Phi\theta\sigma\eta}{\sigma\eta-(r-\rho)\left(1-\eta+\gamma\eta\right)}\right]^{\frac{1}{1-\gamma}}\frac{r-\rho}{\sigma\eta r-(r-\rho)\left(1-\eta+\gamma\eta\right)}<0$$

**Proposition 1** Along the BGP, when other things are held constant, an overall increase in the time devoted to human capital accumulation will decrease the relative human capital of women.

The expression (3.15) can then be substituted into (3.14) to obtain time devoted to education/learning ($\eta$) and work time allocation ($1-\eta$):

$$\eta = \frac{1}{\sigma r + (r-\rho)(1-\gamma)} \left[ \frac{\theta (r-\rho)}{1-\delta I(t \in [M+B, M+B+D])} + r - \rho \right] \tag{3.16}$$

$$1-\eta = 1 - \frac{(r-\rho)\{\theta + [1-\delta I(t \in [M+B, M+B+D])]\}}{[\sigma r + (r-\rho)(1-\gamma)][1-\delta I(t \in [M+B, M+B+D])]}$$

**Proposition 2** When the human capital spillover effect is smaller ($\gamma \uparrow$), when the assortative matching factor is higher ($\theta \uparrow$), and when the labor productivity loss during the years with children attached is more severe ($\delta \uparrow$), a woman will allocate more time to human capital accumulation.

The net work hours ($\ell$) can be computed as follows:

$$\begin{aligned} \ell &= [1-\delta I(t \in [M+B, M+B+D])](1-\eta) \\ &= [1-\delta I(t \in [M+B, M+B+D])] - \frac{(r-\rho)\{\theta + [1-\delta I(t \in [M+B, M+B+D])]\}}{\sigma r + (r-\rho)(1-\gamma)} \end{aligned} \tag{3.17}$$

That is, the hypothetical balanced growth equilibrium value of time devoted to education/learning ($\eta$) can be solved recursively. Once $\eta$ is solved, $v$ and $\ell$ are solved. From (3.17), we find that birth of children has an overall negative effect on work hours due to productivity loss. Moreover, from (3.7) the relative price of human capital investment can be solved. Given initial nonhuman wealth $a_M$ and human capital $h_M$, from (3.12) we obtain the initial consumption at age $M$ as (assuming that the woman does not give birth at age $M$):

$$c(M) = \frac{[\rho + (\sigma - 1) r]}{\sigma} a_M + \left[ \frac{(1+\theta)[\sigma r - \gamma (r-\rho)]}{\sigma r + (r-\rho)(1-\gamma)} \right] A h_M \tag{3.18}$$

Denote $c(M+B)$ as the consumption of the woman when she gives birth to her child. From

(3.12), we can also derive the consumption at age $M+B$:

$$c\left(M+B\right)=\tilde{c}\left(M+B\right)e^{\left(\frac{r-\rho}{\sigma}\right)B}$$

where

$$\tilde{c}\left(M+B\right)=\frac{\left[\rho+\left(\sigma-1\right)r\right]}{\sigma}a_{M}+\left[\frac{\left(1+\theta-\delta\right)\left[\sigma r-\gamma\left(r-\rho\right)\right]}{\sigma r+\left(r-\rho\right)\left(1-\gamma\right)}\right]Ah_{M}$$

That is, $\tilde{c}\left(M+B\right)$ is smaller than $c\left(M\right)$ by $\left[\frac{\delta\left[\sigma r-\gamma\left(r-\rho\right)\right]}{\sigma r+\left(r-\rho\right)\left(1-\gamma\right)}\right]Ah_{M}$. For a woman aged between $[M+B,M+B+D]$ (i.e. for $t\in[M+B,M+B+D]$), her consumption stream along the hypothetical BGP is

$$c\left(t\right)=\tilde{c}\left(M+B\right)e^{\left(\frac{r-\rho}{\sigma}\right)(t-M)}$$

And for women who have not had children yet and whose children already leave the nest ($t\in[M,M+B]\cup[M+B+D,M+F]$), their consumption stream along the hypothetical BGP is

$$\begin{aligned}c(t) &= \left\{\frac{\left[\rho+\left(\sigma-1\right)r\right]}{\sigma}a_{M}+\left[\frac{\left(1+\theta\right)\left[\sigma r-\gamma\left(r-\rho\right)\right]}{\sigma r+\left(r-\rho\right)\left(1-\gamma\right)}\right]\right\}e^{\left(\frac{r-\rho}{\sigma}\right)(t-M)}\\ &= c(M)e^{\left(\frac{r-\rho}{\sigma}\right)(t-M)}\end{aligned}$$

Therefore, the lifetime utility of a woman, a function of $B$, is derived as (see the Appendix for derivations):

$$V\left(B\right)=C_{1}\left(B\right)+C_{2}\left(B\right)+\frac{1}{\rho}\Omega\left(B\right)\tag{3.19}$$

where

$$
\begin{aligned}
C_1(B) &= \frac{c(M)^{1-\sigma}}{1-\sigma}\frac{\sigma}{\rho+(\sigma-1)r}\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]F}-\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right]e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B}\right] \\
C_2(B) &= \frac{\tilde{c}(M+B)^{1-\sigma}}{1-\sigma}\frac{\sigma}{\rho+(\sigma-1)r}\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right]e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B} \\
\Omega(B) &= U_0\left(e^{-\rho B}-e^{-\rho F}\right)-\psi\left(1-e^{-\rho D}\right)e^{-\rho B}
\end{aligned}
$$

Note that $C_1(B)$ is the utility coming from the lifetime without children attached, and $C_2(B)$ is the lifetime utility coming from the period when her children are attached to her. Thus, it is not surprising that $C_1(B)$ an increasing function in $B$ and $C_2(B)$ is a decreasing function in $B$. Due to the productivity loss, $c(M) > \tilde{c}(M+B)$, and hence a birth postponement (higher $B$) will lead to a net utility gain from consumption. Whether $\Omega(B)$ is an increasing or a decreasing function in $B$ depends on the relative magnitude of the utility from having children and the disutility when children are young. To ensure that the woman will consider to have a child ($B^* < \infty$), we have to impose the following condition.

**Condition B** $U_0/\psi > \left(1-e^{-\rho D}\right)$.

Thus, under Condition B, $\Omega(B)$ is a decreasing function in $B$. If Condition B is not satisfied, a woman's lifetime utility will always increase in $B$, meaning that it is optimally for the woman not to have children. However, even when Condition B is satisfied, when the productivity loss is too severe (large $\delta$), it is possible that the optimally chosen age of childbearing $B^* > F$, implying a case of no childbearing. On the contrary, when the net utility enjoyment from having a child is very high (large $U_0$), we have $B^* = 0$, implying childbearing soon after marriage.

### 3.3.4 Main Theoretical Predictions

From second stage optimization over (3.19), an interior child birth timing must satisfy the following first-order condition:

$$\begin{aligned} V'(B) &= \frac{c(M)^{1-\sigma} - \tilde{c}(M+B)^{1-\sigma}}{1-\sigma} \left[1 - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right] e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B} - e^{-\rho B}\left[U_0 - \psi\left(1 - e^{-\rho D}\right)\right] \\ &= \Gamma_1(B) - \Gamma_2(B) \\ &= 0 \end{aligned} \tag{3.20}$$

which illustrates the trade-off in childbearing postponement between productivity gain and net utility gain. It is easy to see that the first term $\Gamma_1(B)$, the net consumption gain from postponing childbearing, is decreasing in $B$. $\Gamma_1(B)$ is also positively depending on productivity loss $\delta$ and negatively depending on husband's income (or income security) $\theta$:

$$\begin{aligned} \frac{d\Gamma_1(B)}{d\delta} &= \left[1 - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right] e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B} \frac{\left[\sigma r - \gamma(r-\rho)\right] Ah_M}{\sigma r + (r-\rho)(1-\gamma)} > 0 \\ \frac{d\Gamma_1(B)}{d\theta} &= \left[1 - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right] e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B} \frac{\left[\sigma r - \gamma(r-\rho)\right] Ah_M}{\sigma r + (r-\rho)(1-\gamma)} \left[c(M)^{-\sigma} - \tilde{c}(M+B)^{-\sigma}\right] < 0 \end{aligned}$$

However, the effect of labor productivity $Ah_M$ on $\Gamma_1(B)$ is less clear:

$$\frac{d\Gamma_1(B)}{dAh_M} = \left[1 - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right] e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B} \left\{ \begin{array}{c} \underbrace{\frac{(1+\theta)\left[\sigma r - \gamma(r-\rho)\right]}{\sigma r + (r-\rho)(1-\gamma)}\left[c(M)^{-\sigma} - \tilde{c}(M+B)^{-\sigma}\right]}_{(-)} \\ + \underbrace{\frac{\delta\left[\sigma r - \gamma(r-\rho)\right]}{\sigma r + (r-\rho)(1-\gamma)}\tilde{c}(M+B)^{-\sigma}}_{(+)} \end{array} \right\}$$

If $\delta$ is big enough, $d\Gamma_1(B)/dAh_M$ is more likely to be positive.[9] Regarding $\Gamma_2(B)$, it is decreasing in $B$ and depends positively on the utility gain of having children $U_0$ and negatively depends on the utility loss when children are attached to mothers.

For illustrative purpose, we shall refer to $\Gamma_1(B)$ and $\Gamma_2(B)$, respectively, as the productivity gain ($PG$) locus and the utility gain ($UG$) locus. It is noted that to have an interior solution of $B$, the second-order condition requires: $V''(B) < 0$, so $\Gamma_1'(B) < \Gamma_2'(B)$, implying that the $UG$ locus is flatter than the $PG$ locus. Figure 3.1 depicts the $PG$ and $UG$ loci over birth timing $B$. As shown in the Appendix, a decrease in preference for quality-adjusted children ($U_0$) or an increase in the utility loss during the childrearing years ($\psi$) shifts the $UG$ locus to the left, whereas an increase in human capital or labor productivity ($Ah_M$) or productivity loss ($\delta$), or a decrease in husband's income or income security ($\theta$) shifts the $PG$ locus to the right. Furthermore, an increase in the duration of childrearing ($D$) shifts the $UG$ locus to the left and the $PG$ locus to the right. Thus, any of such shift leads to a postponement in child birth.

| Effects of an increase in | birth timing ($B$) |
|---|---|
| 1. human capital or labor productivity ($Ah_M$) | $+$ |
| 2. husband's income or income security ($\theta$) | $-$ |
| 3. productivity loss due to childbearing ($\delta$) | $+$ |
| 4. preference for quality-adjusted children ($U_0$) | $-$ |
| 5. utility loss during childrearing years ($\psi$) | $+$ |
| 6. duration of childrearing ($D$) | $+$ |

From (3.20), we can actually solve the optimal age of childbirth $B^*$ directly:

$$B^* = \frac{\sigma}{(\sigma-1)(r-\rho)} \ln \left\{ \frac{c\,(M)^{1-\sigma} - \tilde{c}\,(M+B)^{1-\sigma}}{(1-\sigma)\left[U_0 - \psi\left(1-e^{-\rho D}\right)\right]} \left[1 - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right] \right\}$$

[9] When $\delta$ increases, the first term in the big bracket will be more negative while the second term in the big bracket will be more positive. As long as the second term is more positive, $\frac{d\Gamma_1(B)}{dAh_M} > 0$.

To sum up, changes in human capital or labor productivity ($A$), income security ($\theta$) and productivity loss due to childbearing ($\delta$) represent human capital factors related to fertility decisions. The preference for quality-adjusted children ($U_0$) and the utility loss during childrearing years ($\psi$) capture the fertility and child-loving preference factors in birth timing decision-making, which may even include gender preference and preference of having young children around (i.e., son preference can be captured by a higher value of $U_0$; women who enjoy having young children around would have a lower $\psi$). Our comparative-static results indicate that birth timing is delayed if human capital/labor productivity or productivity loss rises, or if the husband's income/income security or fertility preference falls. Of particular note, labor market conditions are embedded in the human capital factor because wage rates depend positively on the (efficiency unit) human capital measure. These implications can be readily extended to a more general model with multiple births.

These theoretical predictions are useful for guiding our empirical analysis. It is straightforward for women's human capital measured by education levels to be important explanatory variables for the timing of births. While job security can be measured by public employment where job tenure is almost guaranteed, productivity loss due to childbearing can be related to occupations. For instance, financial, managerial and specialist jobs are more likely to suffer larger productivity losses. Finally, while preference factors may be partly captured by family obligations and gender bias (toward son) for married women, they naturally lead to unobserved heterogeneities.

## 3.4 Numerical Analysis

We now want to quantify our theory of birth timing by matching life-cycle model to the Current Population Survey (CPS) data.

### 3.4.1 Calibration

There are 14 parameters from the model. First, we pin down a number of parameters from the literature or directly from the data. Second, we calibrate the remaining parameters using model targets.

We set the inverse of the intertemporal elasticity of substitution $\sigma$, the discounting factor $\rho$, and interest rate $r$ to be the standard values in the literature. For the productivity loss, Waldfogel (1998) claims that the wage loss of child penalty for a women in the United States ranges from 10% to 15%. Since our $\delta$ includes both human capital depreciation and productivity loss, we take the high end to set $\delta = 15\%$. The duration for productivity loss is taken from Phipps et al. (2001), in which they found out that the average duration of child-related interruptions followed by a return to the same job was 1.93 years and the average duration of child-related interruptions followed by a return to a different job was 5.75 years. In their sample, 42.9% went back to the same job, and hence we take a weighted average to set $D = 4.111$ years.

The initial age $M$ is calibrated by using the average age at first marriage of two cohorts from CPS. We assume all women retire at 60 years old, and hence we get the working periods $F$ to be 37.78 years. For husband-to-wife ratio $\theta$, we use gender gap to calibrate, which is defined as the coefficient of the gender dummy variable regressed on log wage earnings, controlling for age, a quartic in age, industry, and states dummies. The coefficients estimated from the wage regressions range from 0.5 to 0.8, depending on the age and marital restrictions we put on the sample. We take the coefficient to be 0.5, in which words, husband-to-wife income ratio is about 1.649. For the technology $A$, the model predicts $A = w$; therefore similar to the estimate of gender gap, we calibrate productivity from the wage regression. First we define a group indicator variable for the two groups that are categorized on skill levels: we define low-skilled group as the females with high school degree and high-skilled group as those with at least some college experience and above. We regress log wages on the group dummy, age, a quartic in age, state dummies, class of workers, broad industry dummies, and broad occupation dummies, in which the base group is low-skilled females, and then we take exponential of the coefficient estimate of the group dummy variable from the regression to get the productivity measure.

We measure human capital following Hall and Jones (1999):

$$h = \exp\{f(s)\}$$

where $h$ denotes human capital, $s$ denotes years of schooling, and $f(s)$ is a piecewise linear function:

$$f(s) = \begin{cases} 0.134s \quad \text{if} \quad s < 4 \\ 0.134 * 4 + 0.101(s-4) \quad \text{if} \quad 4 \leq s \leq 8 \\ 0.134 * 4 + 0.101 * 4 + 0.068(s-8) \quad \text{if} \quad s > 8 \end{cases}$$

The rest of the four parameters $\Phi$, $\gamma$, $U_0$ and $\psi$ are calibrated using model targets. We calibrate average $\eta$ as the ratio of average years of schooling and working period, which is the ratio of 14.24 and 37.78, and then we use equation 3 at the mean to calibrate the maximum human capital accumulation rate $\Phi$ using the average human capital growth rate. For the parameter that governs the human capital spillover effect $\gamma$, we use equation 14 at the mean, intertemporal no arbitrage condition. To calibrate $U_0$ and $\psi$, we target the average fertility timing and fertility timing differential between the high-skilled group and low-skilled group. In order to do that, we need group specific $\delta$ and $D$.

Denote the share of females returning to the same job after child-related interruptions by $\alpha$, and denote the duration of interruption by $\pi$. Denote the share of high-skilled by $S_H$, then the remaining share for the low-skilled group is $1 - S_H$.

$$\bar{\pi} = \alpha\pi_S + (1-\alpha)\pi_D$$

Similarly we define the average duration for the two skill groups:

$$\bar{\pi}_H = \alpha_H\pi_S + (1-\alpha_H)\pi_D$$
$$\bar{\pi}_L = \alpha_L\pi_S + (1-\alpha_L)\pi_D$$

We assume $\alpha_H = 1.2\alpha$ for the high group, and we need to back out $x$ for the low-skilled group such that $\alpha_L = x\alpha$. Since we have:

$$\bar{\pi} = S_H\bar{\pi}_H + (1-S_H)\bar{\pi}_L$$

And hence we have:

$$x = \frac{1-1.2S_H}{1-S_H}$$

In this way, we calibrate $D_H = 3.783$ and $D_L = 4.725$. In a similar fashion, we assume that the human capital depreciation rate of the high-skilled is 1.3 times of the average depreciation rate, and thus we have $\delta_H = 0.195$ and $\delta_L = 0.06573$. Table 3.4 summarizes all the calibrated parameters.

Table 3.4: Calibration parameters

| Parameters | Values | Description | Source/Target |
|---|---|---|---|
| $\sigma$ | 2.5 | inverse of the intertemporal elasticity of substitution | literature |
| $\rho$ | 0.05 | discounting factor | literature |
| $r$ | 12% | interest rate | literature |
| $\delta$ | 15% | productivity loss during childrearing | Waldfogel (1998) |
| $D$ | 4.11 | duration of childrearing | Phipps, Burton, Lethbridge (2001) |
| $M$ | 22.22 | age at marriage | age of first marriage |
| $F$ | 37.78 | working life span | author's calculation |
| $\theta$ | 1.649 | husband to wife log income ratio | gender gap |
| $A_L$ | 1.000 | technology | normalization |
| $A_H$ | 1.240 | technology | wage regression |
| $\Phi$ | 0.0459 | maximum human capital accumulation rate | average human capital growth rate |
| $\gamma$ | 0.9523 | human capital spillover effect | intertemporal no arbitrage condition |
| $U_0$ | 0.00089 | lifetime utility gain from child | fertility timing |
| $\psi$ | 0.00292 | utility loss during childrearing | fertility timing differential |

The following table 3.5 shows model predictions, in which the top panel illustrates the average and the difference between the two skill groups, and the bottom panel illustrates the results for two skill groups. We target the average time allocated to human capital accumulation, the average first spacing and age at first marriage as well as their differentials between skill groups. As can be seen from the table that high-skilled females are more likely to have their first child later in life, and they also allocate more time into human capital accumulation, thus having a higher relative human capital.

Table 3.5: Model Predictions

(a) Average and Difference between Skill Groups

| | | Data | | Model | |
|---|---|---|---|---|---|
| Variable | Description | Average | Diff | Average | Diff |
| $B$ | first spacing | 2.9945 | 0.7313 | 2.9945 | 0.7313 |
| $M+B$ | age at first birth | 25.2166 | 1.0905 | 25.2166 | 1.0905 |
| $\eta$ | human capital allocation | 0.3770 | 0.0910 | 0.3770 | 0.0944 |
| $\nu$ | relative human capital | 1.0000 | 0.2415 | 1.2153 | 5.4016 |
| $l$ | time allocated to work | 0.6230 | -0.0910 | 0.6134 | -0.0098 |

(b) High Skill and Low Skill Group

| | | Data | | Model | |
|---|---|---|---|---|---|
| Variable | Description | High | Low | High | Low |
| $B$ | first spacing | 3.2490 | 2.5178 | 3.2490 | 2.5178 |
| $M+B$ | age at first birth | 25.5962 | 24.5057 | 25.5962 | 24.5057 |
| $\eta$ | human capital allocation | 0.4087 | 0.3176 | 0.4101 | 0.3157 |
| $\nu$ | relative human capital | 1.0840 | 0.8425 | 5.4304 | 0.0288 |
| $l$ | time allocated to work | 0.5913 | 0.6824 | 0.6100 | 0.6198 |

### 3.4.2 Counterfactual Exercises

In order to understand the driving factors behind the divergence of childbirth timing decisions between low-skilled group and high-skilled group, we perform two types of counterfactual experiments. In the first group of experiments we shut down different sources of heterogeneity in the model, including fertility-related productivity loss, initial human capital, productivity, and husband income (income security). Second, we want to examine the effect of fertility preference and leisure loss in the preference. To sum up, we perform 6 counterfactual exercises in total:

1. Sources of heterogeneity

   (a) shut down duration of productivity loss heterogeneity by setting $D_H = D_L = D$

   (b) shut down initial human capital heterogeneity by setting initial $h_H = h_L = h$

   (c) shut down productivity heterogeneity by setting $A_H = A_L = A$

   (d) shut down assortative matching heterogeneity by setting $\tilde{\theta} = \dfrac{\theta \bar{w} \bar{h}}{w_i h_i}$

2. Fertility preference and leisure loss

   (a) increase $U_0$ by 1%

   (b) decrease $\psi$ by 1%

Table 3.6 shows the results for the first group of counterfactual experiments. Let's focus on the 4th column that indicates the implied difference between the high-skilled group and low-skilled group. As can be seen from the first two rows in all the four panels, shutting down heterogeneity in duration of productivity loss leads to a dramatic gap of the first spacing, which is 13.1330 years. However, the effect stemming from the heterogenous initial human capital or productivity (experiment 2 and 3) is much less evident; the difference of first spacing is by 6.6570 and 5.0398 years respectively. The husband income $\theta$, which can be also interpreted as the measure of income security, also plays a critical role in explaining the first spacing differential, which can be seen from the first row in panel (d) that the difference is 13.7079 years. The same pattern holds for the age at first birth, measured by $M + B$. The conventional human capital channel serves a certain role in understanding the childbearing timing; however according to our quantitate result, the two new channels via fertility-related productivity loss and income security are much more essential.

Next table 3.7 illustrates the results for the second group of experiments. We only show the effect of change in $U_0$ and $\psi$ on the first spacing $B$ and the age at first birth $M + B$. The reason why we do not show the corresponding changes in $\eta$, $\nu$, and $l$ is that under these two experiments, the time allocated to human capital accumulation is not affected, and neither is the net working hours. Moreover, a 1% increase in $U_0$ has the same effect on the relative human capital as that of 1% decrease in $\psi$. As can be seen from the 5th and 6th columns in the table, a 1% increase in fertility preference leads to the decrease in the first spacing, 0.5420 and 0.7574 for the high skill group and low skill group respectively. Though a 1% decrease in leisure loss also implies a drop in the first spacing, the effect is not as strong as that shown in panel (a). So we argue that women are sensitive to the changes in fertility preference compared to leisure loss. Another observation from this table is that the decrease for the low-skilled group is much more pronounced than that for the high-skilled group, which implies that the low-skilled women are more vulnerable to the changes in fertility preference and leisure loss.

Table 3.6: Sources of heterogeneity

(a) Experiment 1: $D_H = D_L = D$

| | | | | Relative to Benchmark Model | |
|---|---|---|---|---|---|
| Variable | High Skilled | Low Skilled | Difference | High Skilled | Low Skilled |
| $B$ | 7.4425 | -5.6905 | 13.1330 | 4.1935 | -8.2083 |
| $M + B$ | 29.7897 | 16.2974 | 13.4923 | 4.1935 | -8.2083 |
| $\eta$ | 0.3782 | 0.3748 | 0.0034 | -0.0319 | 0.0591 |
| $\nu$ | 0.9612 | 1.0760 | -0.1148 | -4.4692 | 1.0472 |
| $l$ | 0.6086 | 0.6207 | -0.0122 | -0.0015 | 0.0009 |
| $\Delta V(B)/V(B)$ | -0.0058 | 0.0053 | -0.0111 | | |

(b) Experiment 2: $h_H = h_L = h$

| | | | | Relative to Benchmark Model | |
|---|---|---|---|---|---|
| Variable | High Skilled | Low Skilled | Difference | High Skilled | Low Skilled |
| $B$ | 5.1137 | -1.5433 | 6.6570 | 1.8647 | -4.0611 |
| $M + B$ | 27.4609 | 20.4446 | 7.0163 | 1.8647 | -4.0611 |
| $\eta$ | 0.3778 | 0.3751 | 0.0027 | -0.0323 | 0.0594 |
| $\nu$ | 0.9743 | 1.0670 | -0.0927 | -4.4561 | 1.0382 |
| $l$ | 0.6100 | 0.6198 | -0.0098 | 0.0000 | 0.0000 |
| $\Delta V(B)/V(B)$ | -0.0996 | 0.1807 | -0.2803 | | |

(c) Experiment 3: $A_H = A_L = A$

| | | | | Relative to Benchmark Model | |
|---|---|---|---|---|---|
| Variable | High Skilled | Low Skilled | Difference | High Skilled | Low Skilled |
| $B$ | 4.6440 | -0.3958 | 5.0398 | 1.3949 | -2.9136 |
| $M + B$ | 26.9912 | 21.5921 | 5.3991 | 1.3949 | -2.9136 |
| $\eta$ | 0.3778 | 0.3751 | 0.0027 | -0.0323 | 0.0594 |
| $\nu$ | 0.9743 | 1.0670 | -0.0927 | -4.4561 | 1.0382 |
| $l$ | 0.6100 | 0.6198 | -0.0098 | 0.0000 | 0.0000 |
| $\Delta V(B)/V(B)$ | -0.1721 | 0.1336 | -0.3057 | | |

(d) Experiment 4: change in $\theta$

| | | | | Relative to Benchmark Model | |
|---|---|---|---|---|---|
| Variable | High Skilled | Low Skilled | Difference | High Skilled | Low Skilled |
| $B$ | 7.2827 | -6.4252 | 13.7079 | 4.0336 | -8.9430 |
| $M + B$ | 29.6299 | 15.5627 | 14.0672 | 4.0336 | -8.9430 |
| $\eta$ | 0.3486 | 0.4486 | -0.1000 | -0.0615 | 0.1329 |
| $\nu$ | 0.1804 | 45.5108 | -45.3304 | -5.2500 | 45.4820 |
| $l$ | 0.6387 | 0.5469 | 0.0918 | 0.0286 | -0.0729 |
| $\Delta V(B)/V(B)$ | -0.1775 | 0.2026 | -0.3800 | | |

Table 3.7: Fertility preference and leisure loss

(a) Experiment 5: 1% increase in $U_0$

| | | | | Relative to Benchmark Model | |
|---|---|---|---|---|---|
| Variable | High Skilled | Low Skilled | Difference | High Skilled | Low Skilled |
| $B$ | 2.7070 | 1.7604 | 0.9467 | -0.5420 | -0.7574 |
| $M+B$ | 25.0542 | 23.7483 | 1.3059 | -0.5420 | -0.7574 |

(b) Experiment 6: 1% decrease in $\psi$

| | | | | Relative to Benchmark Model | |
|---|---|---|---|---|---|
| Variable | High Skilled | Low Skilled | Difference | High Skilled | Low Skilled |
| $B$ | 2.9409 | 1.9922 | 0.9488 | -0.3081 | -0.5256 |
| $M+B$ | 25.2881 | 23.9801 | 1.3080 | -0.3081 | -0.5256 |

### 3.4.3 Decomposition

In this section, we perform the decomposition exercise to further understand the precise contribution of each channel to the childbirth timing decisions for two skill groups. Since the analysis on the age at first birth (M+B) and the first spacing (B) is the same, we only present results for the first spacing here, as illustrated by the following table 3.8.

The assortative matching channel, measured by the husband income $\theta$, is able to explain 53.12% of the average first spacing. Initial divergence in human capital can account for 21.76%. However, the conventional human capital and productivity channel together can only contribute to around 33% of the total gap, which implies the crucial role that the income security and duration channel plays.

The result is even more interesting if we focus on the implied difference between the high-skilled group and low-skilled group. Heterogeneity in initial human capital and productivity together explain less than one third of the gap, of which the effect is much less pronounced than that from the experiment 1 and experiment 4. The heterogeneity in duration of fertility-related productivity loss along can explain around 34.82% of the difference between high-skilled group and low-skilled group. The remaining 36.44% of the gap is attributed to the income security channel. The decomposition exercise reinforces our finding that the novel productivity loss and income security channels play a much more crucial role than the conventional human capital and productivity channel in understanding the childbearing timing, especially the differences in the childrearing timing decisions between skill groups.

Table 3.8: Decomposition: First Spacing (B)

| | Average | | | Difference | | |
|---|---|---|---|---|---|---|
| | result | normalized | contribution | result | normalized | contribution |
| model | 2.9945 | | | 0.7313 | | |
| Exp1: duration | 2.8707 | 0.4070 | 13.59% | 13.1330 | 0.2547 | 34.82% |
| Exp2: initial human capital | 2.7963 | 0.6571 | 21.76% | 6.6570 | 0.1217 | 16.64% |
| Exp3: productivity | 2.8895 | 0.3451 | 11.52% | 5.0398 | 0.0885 | 12.10% |
| Exp4: assortative matching | 2.5107 | 1.5907 | 53.12% | 13.7079 | 0.2665 | 36.44% |
| SUM | | | 100% | | | 100% |

## 3.5 Extensions

Up so far, we have examined the influence of different sources of heterogeneity, fertility preference and leisure loss on the fertility timing differential between skill groups. In the next step, using data for the two cohorts, we will be able to compare the relative importance of the factors such as improvement in initial human capital, delay in marriage, narrower gender gap, and rising college premium. Instead of focusing on only two skill groups, we can further analyze the evolution of birth distribution. Last but not least, we can conduct robustness check using the census data for the early cohort allowing for multiple number of children and multiple spacing.

## 3.6 Conclusion

This paper has developed a life-cycle model of fertility choice that theoretically identifies key factors driving a woman's decision regarding on the timing of childbearing that is modeled as a continuous variable. On top of the conventional human capital channel and fertility preference, this paper highlights the importance of the duration of fertility-related productivity loss, income security, and leisure loss. Numerical analysis implies that in terms of explaining the gap of first spacing and age at first birth between the two skill groups, duration of productivity loss and income security have played a much more crucial role compared to education or opportunity cost. The conventional human capital together with productivity channel can account for only 28.7% of the gap, while around 34.8% of the difference between high-skilled women and low-skilled women can be explained by the duration of fertility-related productivity loss and the remaining 36.4% can be attributed to the income security (husband's income) channel. Moreover, both the low-skilled group and the high-skilled group are more sensitive to changes in child preference when determining the timing of the birth, and the low-skilled women are more vulnerable to changes in productivity and fertility preference, which explains why low-skilled women push up or defer their timing of children more relative to high-skilled women.

## 3.7 Appendix (Not intended for publication)

*Derivation of lifetime utility*

$$
\begin{aligned}
V(B) &= \int_M^{M+F} \left[\frac{c^{1-\sigma}}{1-\sigma} + U_0 I(t \in [M+B, M+F]) - \psi I(t \in [M+B, M+B+D])\right] e^{-\rho(t-M)} dt \\
&= \int_M^{M+F} \frac{c^{1-\sigma}}{1-\sigma} e^{-\rho(t-M)} dt + U_0 \int_M^{M+F} I(t \in [M+B, M+F]) e^{-\rho(t-M)} dt \\
&- \psi \int_M^{M+F} I(t \in [M+B, M+B+D]) e^{-\rho(t-M)} dt \\
&= (i) + (ii) + (iii)
\end{aligned}
$$

$$
\begin{aligned}
(i) &= \int_M^{M+F} \frac{c^{1-\sigma}}{1-\sigma} e^{-\rho(t-M)} dt \\
&= \int_M^{M+B} \frac{c^{1-\sigma}}{1-\sigma} e^{-\rho(t-M)} dt + \int_{M+B}^{M+B+D} \frac{c^{1-\sigma}}{1-\sigma} e^{-\rho(t-M)} dt + \int_{M+B+D}^{M+F} \frac{c^{1-\sigma}}{1-\sigma} e^{-\rho(t-M)} dt \\
&= (A) + (B) + (C)
\end{aligned}
$$

$$
\begin{aligned}
(A) &= \int_M^{M+B} \frac{c(M)^{1-\sigma} e^{(1-\sigma)\left(\frac{r-\rho}{\sigma}\right)(t-M) - \rho(t-M)}}{1-\sigma} dt \\
&= \frac{c(M)^{1-\sigma}}{1-\sigma} \int_M^{M+B} e^{-(t-M)\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]} dt \\
&= \frac{c(M)^{1-\sigma}}{1-\sigma} \frac{\sigma}{\rho + (\sigma-1) r} \left[1 - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right] B}\right]
\end{aligned}
$$

$$
\begin{aligned}
(B) &= \int_{M+B}^{M+B+D} \frac{\tilde{c}(M+B)^{1-\sigma} e^{(1-\sigma)\left(\frac{r-\rho}{\sigma}\right)(t-M) - \rho(t-M)}}{1-\sigma} dt \\
&= \frac{\tilde{c}(M+B)^{1-\sigma}}{1-\sigma} \int_{M+B}^{M+B+D} e^{-(t-M)\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]} dt \\
&= \frac{\tilde{c}(M+B)^{1-\sigma}}{1-\sigma} \frac{\sigma}{\rho + (\sigma-1) r} \left[e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right] B} - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right](B+D)}\right]
\end{aligned}
$$

$$
\begin{aligned}
(C) &= \frac{c(M)^{1-\sigma}}{1-\sigma}\int_{M+B+D}^{M+F} e^{-(t-M)\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]}dt \\
&= \frac{c(M)^{1-\sigma}}{1-\sigma}\frac{\sigma}{\rho+(\sigma-1)\,r}\left[e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right](B+D)} - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]F}\right]
\end{aligned}
$$

Hence,

$$
\begin{aligned}
(i) &= \frac{c(M)^{1-\sigma}}{1-\sigma}\frac{\sigma}{\rho+(\sigma-1)\,r}\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]F} - \left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right]e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B}\right] \\
&\quad + \frac{\tilde{c}\,(M+B)^{1-\sigma}}{1-\sigma}\frac{\sigma}{\rho+(\sigma-1)\,r}\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right]e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B}
\end{aligned}
$$

$$
\begin{aligned}
(ii) &= U_0\int_{M}^{M+F} I(t\in[M+B,M+F])e^{-\rho(t-M)}dt \\
&= U_0\int_{M+B}^{M+F} e^{-\rho(t-M)}dt \\
&= \frac{U_0}{\rho}\left(e^{-\rho B}-e^{-\rho F}\right) \\
(iii) &= \psi\int_{M}^{M+F} I(t\in[M+B,M+B+D])e^{-\rho(t-M)}dt \\
&= \psi\int_{M+B}^{M+B+D} e^{-\rho(t-M)}dt \\
&= \frac{\psi}{\rho}\left[e^{-\rho B}-e^{-\rho(B+D)}\right] \\
&= \frac{\psi}{\rho}\left[1-e^{-\rho D}\right]e^{-\rho B}
\end{aligned}
$$

Therefore, the lifetime utility, a function of $B$, is derived as

$$\begin{aligned} V(B) &= \frac{c(M)^{1-\sigma}}{1-\sigma}\frac{\sigma}{\rho+(\sigma-1)r}\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]F}-\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right]e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B}\right] \\ &\quad +\frac{\tilde{c}\left(M+B\right)^{1-\sigma}}{1-\sigma}\frac{\sigma}{\rho+(\sigma-1)r}\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right]e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B} \\ &\quad +\frac{U_0}{\rho}\left(e^{-\rho B}-e^{-\rho F}\right)-\frac{\psi}{\rho}\left[1-e^{-\rho D}\right]e^{-\rho B} \\ &= C_1\left(B\right)+C_2\left(B\right)+\frac{1}{\rho}\Omega\left(B\right) \end{aligned}$$

where

$$C_1\left(B\right)=\frac{c(M)^{1-\sigma}}{1-\sigma}\frac{\sigma}{\rho+(\sigma-1)r}\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]F}-\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right]e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B}\right]$$

$$C_2\left(B\right)=\frac{\tilde{c}\left(M+B\right)^{1-\sigma}}{1-\sigma}\frac{\sigma}{\rho+(\sigma-1)r}\left[1-e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right]e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B}$$

and

$$\begin{aligned} \Omega\left(B\right) &= U_0\left(e^{-\rho B}-e^{-\rho F}\right)-\psi\left(1-e^{-\rho D}\right)e^{-\rho B} \\ &= \left[U_0\left(1-e^{-\rho(F-B)}\right)-\psi\left(1-e^{-\rho D}\right)\right]e^{-\rho B} \end{aligned}$$

*Derivation of Condition B*

To derive Condition B, we differentiate $\Omega\left(B\right)$ with respect to $B$:

$$\begin{aligned} \Omega'\left(B\right) &= -\rho U_0 e^{-\rho B}+\rho\psi\left(1-e^{-\rho D}\right)e^{-\rho B} \\ &= \rho e^{-\rho B}\left[-U_0+\psi\left(1-e^{-\rho D}\right)\right] \end{aligned}$$

Therefore,

$$\Omega'\left(B\right)\gtreqless 0 \quad \text{if} \quad \frac{U_0}{\psi}\lesseqgtr\left(1-e^{-\rho D}\right)$$

To ensure that a $V(B)$ is strictly concave in $B$, we thus impose the condition $\frac{U_0}{\psi} > \left(1 - e^{-\rho D}\right)$.

*Derivation of the first-order condition*

$$
\begin{aligned}
V'(B) &= C_1'(B) + C_2'(B) + \frac{1}{\rho}\Omega'(B) \\
&= \frac{c(M)^{1-\sigma}}{1-\sigma}\left[1 - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right] e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B} - \frac{\tilde{c}(M+B)^{1-\sigma}}{1-\sigma}\left[1 - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right] e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B} \\
&\quad - e^{-\rho B}\left[U_0 - \psi\left(1 - e^{-\rho D}\right)\right] \\
&= \frac{c(M)^{1-\sigma} - \tilde{c}(M+B)^{1-\sigma}}{1-\sigma}\left[1 - e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]D}\right] e^{-\left[\frac{\rho+(\sigma-1)r}{\sigma}\right]B} - e^{-\rho B}\left[U_0 - \psi\left(1 - e^{-\rho D}\right)\right] \\
&= \Gamma_1(B) - \Gamma_2(B) \\
&= 0
\end{aligned}
$$

The original formulation of $L$:

$$
L = \int_{M=t-F}^{t} \int_{i \,\in\, \text{cohort } M} \{[1 - \delta I(t \in [M+B, M+B+D])](1-\eta)h\}\, di dM
$$

*Derivation of the comparative statics:* Recall the definitions of $\Omega(B)$ and $\Lambda(B)$:

$$
\begin{aligned}
\Omega(B) &= \left[U_0\left(1 - e^{-\rho(F-B)}\right) - \psi\left(1 - e^{-\rho D}\right)\right] e^{-\rho B} \\
\Lambda(B) &= [1 - \delta I(t \in [M+B, M+B+D])] - \frac{r^{1-\gamma}(r-\rho)^{\gamma}}{\sigma^{\gamma}(1-\gamma)^{1-\gamma}\Phi}
\end{aligned}
$$

Straightforward differentiation yields:

$$
\begin{aligned}
\Omega'(B) &= -\rho e^{-\rho B}\left[U_0 - \psi\left(1 - e^{-\rho D}\right)\right] < 0 \\
\Omega''(B) &= \rho^2 e^{-\rho B}\left[U_0 - \psi\left(1 - e^{-\rho D}\right)\right] > 0
\end{aligned}
$$

which implies:

$$\Gamma_2'(B) = -\rho e^{-\rho B}\left[U_0 - \psi\left(1 - e^{-\rho D}\right)\right] < 0$$

Moreover, from the property of the indicator functions, we have: $\Lambda'(B) > 0$ and $\Lambda''(B) = 0$, implying:

$$\begin{aligned} & \frac{d}{dB}\left\{\frac{[\rho + (\sigma-1)\,r]}{\sigma}a_M + [\Lambda(B)+\theta]\,Ah_M\right\}^{-\sigma} Ah_M\Lambda'(B) \\ = \quad & -\sigma\left\{\frac{[\rho + (\sigma-1)\,r]}{\sigma}a_M + [\Lambda(B)+\theta]\,Ah_M\right\}^{-\sigma-1}\left[Ah_M\Lambda'(B)\right]^2 Ah_M < 0 \end{aligned}$$

and hence $\Gamma_1'(B) < 0$. Furthermore, we can derive:

$$\frac{d}{d\theta}\left\{\frac{[\rho + (\sigma-1)\,r]}{\sigma}a_M + [\Lambda(B)+\theta]\,Ah_M\right\}^{-\sigma} Ah_M\Lambda'(B) < 0$$

$$\begin{aligned} & \frac{d}{d\delta}\left\{\frac{[\rho + (\sigma-1)\,r]}{\sigma}a_M + [\Lambda(B)+\theta]\,Ah_M\right\}^{-\sigma} Ah_M\Lambda'(B) \\ = \quad & -\sigma\left\{\frac{[\rho + (\sigma-1)\,r]}{\sigma}a_M + [\Lambda(B)+\theta]\,Ah_M\right\}^{-\sigma-1}\left[Ah_M\Lambda'(B)\right]^2 \frac{\partial\Lambda(B)}{\partial\delta} > 0 \end{aligned}$$

which yield the comparative static results in Section 3.4.

Figure 3.1: Comparative Statics

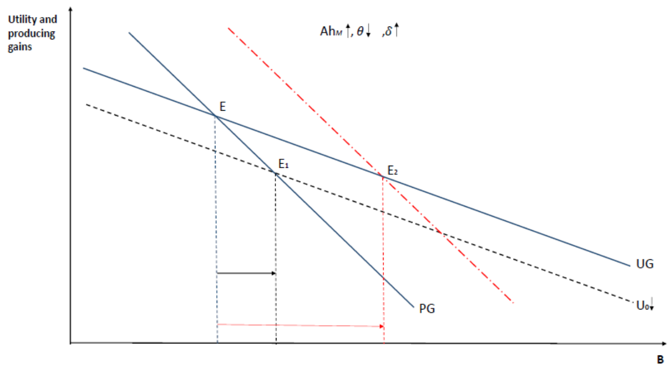


Figure 1: Comparative Statics

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# Conclusion

In this dissertation, I utilize detailed micro-level evidence to understand and issues in the macroeconomics aspects of the labor market, economic demography, human capital, and entrepreneurship. My dissertation focuses on two broad questions: (1) how changes in the labor market affect family structures and shape females' marital choices and fertility decisions and (2) how income inequality interacts with entrepreneurial entry.

The United States has been experiencing a long-term decline in the rates of marriage and fertility and a steady rise in cohabitation. In chapter 1, "**Cohabitation, Marriage, and Fertility: Divergence between Different Skill Groups**", I use data from CPS to show how these patterns vary across education groups: Skilled females have experienced a less pronounced drop in marriage and fertility, while unskilled females have experienced a more evident increase in cohabitation. In the 1980s, 79.8% of unskilled females between 40 and 45 years old were currently married; this number dropped to 64.3% in 2008. For skilled females, the marriage rate declined from 80% in 1980 to 74.9% in 2008. Fertility dropped by 23.5% and 15.6%, respectively, over the same period. Cohabitation increased from 2.82% and 1.75% in 1995 to 5.63% and 3.41% in 2008 for the skilled and the unskilled. These facts challenge the standard theory that emphasizes the opportunity cost of childrearing from labor market and gender specialization.

I propose the following mechanisms to understand this puzzle: For high-skill females, the higher implicit return of investment in children's human capital compensates for part of the growing opportunity cost of childrearing; a significant income effect from positive assortative matching dominates the conventional wage channel; and when childrearing resource cost increases, a strong selection effect exists whereby those with strong fertility motives shift into marriage. To quantitatively discipline the relative importance of different factors, I theorize the tradeoff between market work and childrearing activities by examining decisions on consumption, marital status, and fertility. Calibrating the benchmark model using targets from 1995 to 2008, I am able to capture both within-group fertility rates and between-group fertility differentials. Counterfactual exercises show that 34.81% of the rise in cohabitation and 42.42% of the drop in marriage for the skilled can be explained by the rising returns of children, and 38.06% and 40.07%, respectively, for the unskilled. In addition to the returns of children, rising childrearing cost plays a significant role in explaining the declining fertility rates, contributing to 90.96% and 50.79% of the drop in fertility for the two skill groups. Most of the shrinking cohabitation gap and widened marriage gap between the two skill groups can be attributed to the rising wage and skill premium, increasing childrearing costs, and the growing returns of children; three channels together contribute to around 165.8% of the marriage differentials, while partner's commitment together with cohabitation preference attributes to negative 65.8%.

In chapter 2, "**Skill Biased Entrepreneurial Decline**", my coauthor and I study the forces behind the decline of firm startups in the United States since the late 70s. We document that this slowdown in entrepreneurship is more pronounced for skilled individuals. Between 1983 and 2006, entry into entrepreneurship declined by 11% for those with at least a college degree and increased by 18% for those with at most a high school degree. We posit that this skill-biased entrepreneurial decline is driven by the changing income structure of workers and entrepreneurs over the same period. We show that entrepreneurial income grew more slowly than workers' income for skilled individuals, while for unskilled individuals, both incomes grew at similar rates. To quantify the impact of income structure on entrepreneurial entry, we present a heterogeneous agent occupational choice model that features skill-biased technical change. In the model, the rising skill premium can account for around two-thirds of the observed change in the entry of skilled and unskilled individuals. Our findings emphasize the importance of rising income inequality in understanding the skill-biased decline in entrepreneurship and the broader decline in business dynamism in the United States.

In chapter 3, "**The Timing of Childbearing: Theory and Quantitative Analysis**", my coauthors and I attempt to understand the rise in the age at first birth both theoretically and empirically. We develop a continuous-time lifecycle model in which a married woman decides when to have her first child and how she allocates her time to human capital accumulation and market activity. We find that fertility-related productivity loss and job security play a more important role than the conventional human capital channel in explaining the childbearing timing differentials between skill groups, and that women are more sensitive to changes in fertility preference than to leisure loss. Compared with high-skilled women, low-skilled women are more vulnerable to changes in labor productivity, husband's income, fertility preference for children and leisure loss when raising children. As a result, low-skilled women push up or defer their timing of childbirth more relative to high-skilled women.

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